A Graph Theory-Based Modeling of Functional Brain Connectivity Based on EEG: A Systematic Review in the Context of Neuroergonomics

LINA ELSHERIF ISMAIL [ID] **AND WALDEMAR KARWOWSKI** [ID]**, (Senior Member, IEEE)**
Computational Neuroergonomics Laboratory, Department of Industrial Engineering and Management Systems, University of Central Florida,
Orlando, FL 32816, USA

Corresponding authors: Lina Elsherif Ismail (linaelsherif@knights.ucf.edu) and Waldemar Karwowski (wkar@ucf.edu)

ABSTRACT Graph theory analysis, a mathematical approach, has been applied in brain connectivity studies to explore the organization of network patterns. The computation of graph theory metrics enables the characterization of the stationary behavior of electroencephalogram (EEG) signals that cannot be explained by simple linear methods. The main purpose of this study was to systematically review the graph theory applications for mapping the functional connectivity of the EEG data in neuroergonomics. Moreover, this article proposes a pipeline for constructing an unweighted functional brain network from EEG data using both source and sensor methods. Out of 57 articles, our results show that graph theory metrics used to characterize EEG data have attracted increasing attention since 2006, with the highest frequency of publications in 2018. Most studies have focused on cognitive tasks in comparison with motor tasks. The mean phase coherence method, based on the "phase-locking value," was the most frequently used functional estimation technique in the reviewed studies. Furthermore, the unweighted functional brain network has received substantially more attention in the literature than the weighted network. The global clustering coefficient and characteristic path length were the most prevalent metrics for differentiating between global integration and local segregation, and the small-worldness property emerged as a compelling metric for the characterization of information processing. This review provides insight into the use of graph theory metrics to model functional brain connectivity in the context of neuroergonomics research.

INDEX TERMS Brain connectivity, cognitive functions, clustering coefficient, EEG, functional connectivity, graph theory, motor processing, neuroergonomics.

I. INTRODUCTION

The brain is the most complex organ in the human body, composed of 100 billion neurons connected by almost 150 trillion synapses [1], [2]. Over the last few decades, mapping of the human brain connectivity has gained considerable attention in the areas of neuroscience and cognitive neuroscience [3]–[7]. Modern network science, a mixture of dynamic systems theory, graph theory, and statistics, has been applied to the study of the functional and structural brain connectivity network under various states and conditions. Efforts have been made to study the topological properties of the brain for neurological disorder networks [8], brain disease and dysfunction networks [9]–[11], aging

The associate editor coordinating the review of this manuscript and approving it for publication was Kang Li [ID].

networks [9], resting-state network [12], and high brain function networks such as perception, problem-solving, memory, and attention [13]–[16].

The graph theory approach, a powerful mathematical tool [17], graphically illustrates a complex network architecture based on the modern theory of networks. In 1736, the physicist Leonard Euler solved the problem of crossing the Pregel River, which is known as the "Seven Bridges of Königsberg." The aim was to cross the seven bridges that connected two small islands in the Pregel River to the city of Königsberg only once and to return to the original location using an abstract representation and eliminating all features except for the landmasses and the bridges connecting them. In modern terms, Euler replaced each landmass with an abstract point (i.e., "vertex" or "node") and each bridge with an abstract connection ("edge" or "line"), resulting

TABLE 1. The classification of brain signals by frequency range with descriptions, psychological and behavioral conditions, and location in the brain.

Brain signal	Frequency range	Description	Psychological and behavioral conditions	Brain location
Delta (δ)	0.5 to 4 Hz	- The slowest brain wave regarding the frequency - The highest amplitude - Represents the gray matter - Dominant in infants	- Dominant during the deep sleep stage	- Posterior region in children - Frontal region in adults
Theta (θ)	4 to 8 Hz	- Known as a slow activity - Normal in children up to age 13, while abnormal in awake adults	- Dominant during deep relaxation, meditation, and dreaming in light sleep	- Thalamic region
Alpha (α)	8 to13 Hz	- Represents white matter - Found in all ages	- Dominant in wakeful but relaxed states with closed eyes (i.e., calm) Mainly appears in drowsiness conditions - Disappears when eyes are open	- Posterior regions
Beta (β)	13 to 30 Hz	- A fast wave but not the fastest	- Dominant in alertness, concertation, attention, anxiety, thinking, and calculating - Associated with behavioral tasks such as problem-solving, task engagement, and decision-making	- Parietal and frontal regions
Lower Gamma (γ)	30 to 80 Hz	- The fastest brain frequency signal	- Dominant during high-level cognitive tasks - Related to perception, learning, and language processing	- Somatosensory cortex
Upper Gamma (γ)	80 to 150 Hz			

in a mathematical structure called a "graph" or "network." The contemplation of this problem led to the foundations of "graph theory" — the first true proof in the theory of networks. In 1741, Euler published his paper 'Solutio problematis ad geometriam situs pertinentis,' describing a hypothetical solution to the Konigsberg bridge problem [18].

Graph theory has since become a vital method in the field of electrical circuits and chemical structures. The modern era of graph theory began in the late 1990s with the discovery of small-worldness [19] and scale-free network models [20], enabling the quantification of brain connectivity patterns. Graph theory metrics are used to investigate the topological organization of the brain network and to characterize meaningful functional segregation and integration of the human brain.

The purpose of a systematic review is to identify, summarize, and analyze the findings of all relevant individual studies that address a predefined research question. The preferred reporting items for systematic reviews and meta-analyses (PRISMA) is a structured guideline to ensure reliable and meaningful review results. The protocol consists of 27 checklist items that help researchers to prepare and report evidence accurately and reliably, which in turn improves the quality of research [21]. The present study focuses on understanding the current state of knowledge regarding the applications of graph theory analysis in the context of neuroergonomics. Neuroergonomics, the study of the brain and behavior at work, applies methods and tools from neuroscience to elucidate neural signatures of human performance [22]–[24].

The brain possesses five different types of waves, and a variety of classifications of brain signals are available in the literature [25]–[27]. The most widely used taxonomy is based on the five frequencies of the brain waves measured in Hertz (Hz) as follows: delta (0.5−4 Hz), theta (4−8 Hz), alpha (8−13 Hz), beta (13−30 Hz), and gamma (30−150 Hz) [27]. Table 1 summarizes the information regarding the different types of brain signals according to their frequency ranges, with descriptions of the psychological and behavioral conditions [28]–[30].

The human brain is composed of four main parts: the cerebrum, cerebellum, brainstem, and diencephalon, which together control all bodily functions. Possessing the largest number of neurons, the cerebrum has four main lobes: the frontal, temporal, partial, and occipital lobes, each of which performs a specific function. The frontal lobe is associated with reasoning, movement, planning, emotion, and problem-solving. In contrast, the parietal lobe is associated with movement, recognition, and the perception of stimuli. The temporal lobe is associated with memory, speech, and the recognition of auditory stimuli, whereas the occipital lobe is related to visual responses [27], [29]–[35]. Information transfer among different brain regions reflects a combination of locally segregated and functionally integrated processes [36].

The "connectome" refers to the connectivity among different brain regions and the manner by which information is transferred among these regions [7], [37]. Three different types of connectivity are closely related: structural, functional, and effective connectivity [38], [39]. Structural connectivity encompasses the physical connections among neurons, known as "neuroanatomical" connections [40], which refers to the white matter connectivity in the brain. Functional connectivity is "the statistical interdependencies

between physiological time series recorded from different brain regions'' [41], [42]. Effective connectivity refers to the causal effect and the direct influence of one neural element on another [41], [43], [44]. Functional and effective connectivities are determined by sampling recorded signals over multiple time points, which provides a better understanding of brain function. For a review of functional and effective connectivity, we refer the reader to Friston *et al.* [41], Friston [42] and [45], and Goldenberg and Galván [46].

Continuous efforts in the neuroergonomics field have been devoted to studying the brain signals at work and in everyday settings [22], [23]. The number of useful analytical approaches used in neuroergonomics research is rapidly expanding; however, the functional brain connectivity and network topology in the context of neuroergonomics is largely unknown. Brain networks are typically modeled from data collected by different neuroimaging techniques. Modern electroencephalogram (EEG) systems are noninvasive, portable, wireless, and easy to use, rendering them attractive and applicable to neuroergonomics studies [47]. A considerable amount of work in functional connectivity studies has focused on the blood oxygenation level mainly by functional magnetic resonance imaging (fMRI) [3], [48], [49] due to its good spatial resolution. However, this technique has low temporal resolution and only provides an indirect measurement of brain activity. To study dynamic cognitive processes and the directional flow of information regarding brain activity, a high temporal resolution technique, such as EEG, enables capturing of the temporal dynamics of brain activity at the sub-second time scale [50], [51] and reflects the rapid changes in neuronal states [52]. Furthermore, EEG is capable of capturing the rich temporal information that aids identification of the directions of the flow of information among different brain regions (i.e., causal inference) [53].

Over the last two decades, EEG connectivity has gained considerable interest in clinical studies. The first application of graph theory to EEG data was reported by Stam *et al.* [54], who compared the functional brain network of control individuals and patients with Alzheimer's disease. However, little is known regarding healthy participants during everyday activity. Since the emergence of neuroergonomics, research attempting to characterize EEG data has been limited to the traditional analysis of EEG signals using individual electrodes, and the interdependencies among different EEG electrodes have been poorly addressed [55], [56].

Previous studies have succeeded in quantifying human states under a great variety of cognitive [57] and physical [58] tasks; nevertheless, further work is required to understand the dynamic temporal interactions among brain regions during everyday tasks. Accordingly, the current study sought to review patterns of brain connectivity using the computation of graph theory metrics in task-evoked EEG data.

In contrast to previous reviews [9], [44], we have restricted the current review to EEG studies that utilized the functional brain connectivity data in healthy participants relevant to the field of neuroergonomics. Furthermore, we summarized the pipeline for the construction of a functional network for EEG data. The primary focus of the current systematic review was to provide a framework that will facilitate the application of functional brain network analyses in the field of neuroergonomics in the near future. The present paper is organized as follows: Section II, Methods, presents the standards, search strategy, and eligibility criteria used for selection of the articles evaluated in the current review, as well as the extraction and synthesis of data and validity risk assessment; Section III, Theoretical Background, defines functional connectivity and the basic concepts of graph theory. This section also describes the pipeline for the construction of the functional brain network based on EEG data and discusses the different types of networks using a mathematical description of network measurements to characterize global and nodal brain connectivity; Section IV, Results, provides the results of the systematic literature search, the study characteristics, and a validity assessment of the considered studies; Section V, Discussion, discusses the applications of graph theory in cognitive functions and motor processing; and finally, Section VI, Limitations and Future Directions, outlines the current limitations and provides suggestions for future research.

II. METHODS
A. REVIEW STANDARDS
This systematic review was conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines [21], [59], [60]. Articles were selected based on several research questions, and the search strategy was designed to reduce the effect of research expectations on the current review. The Cochrane Collaboration method was used to minimize the risk of bias, according to Higgins *et al.* [61].

B. RESEARCH QUESTIONS (RQs)
●RQ1: With the advent of graph theory, what applications have been used to model human cognition and motor processing?

●RQ2: How can computational methods be used to characterize the underlying neural mechanisms of cognitive function and motor processing?

●RQ3: What does EEG add to the connectome?

●RQ4: How can an undirected, unweighted functional brain network be modeled using EEG data?

●RQ5: Is the graph theory approach useful for characterizing the underlying neural mechanisms of human cognition and movement as measured by EEG in comparison with traditional approaches?

●RQ6: How can computational methods for modeling patterns of brain connectivity be implemented in neuroergonomics?

C. SEARCH STRATEGY

Comprehensive literature searches were independently conducted using the following databases and search engines: Google Scholar, Science Direct, IEEE Xplore, SpringerLink, Ergonomics Abstracts, and ProQuest, with no limitations on publication year. Firstly, we applied the following Boolean operators: ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network.'' This search resulted in a total of 5,429 articles from Science Direct (n = 2,159), Google Scholar (n = 2149), SpringerLink (n = 544), IEEE (n = 489), ProQuest (n = 50), and Ergonomics Abstracts (n = 38). Subsequently, duplicate articles were removed, resulting in 4,929 records.

D. STUDY SELECTION

Due to the massive number of results obtained from the previous search terms, more keywords with Boolean operators were applied, with no restrictions on publication date, as follows:

- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''cognitive function'' OR ''cognitive work'' OR ''cognitive task'' OR ''cognitive performance.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''physical work'' OR ''physical task'' OR ''physical performance'' OR ''physical activity'' OR ''motion'' OR ''motor'' OR ''exercise.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''fatigue.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''workload.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''working memory.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''perception.''
- ''electroencephalography'' OR ''EEG'' AND ''graph theory'' OR ''functional connectivity'' OR ''brain network'' AND ''exertion.''

These keywords helped to maintain our focus and narrowed the final selection of studies by excluding an additional 3,784 articles. After independently reviewing all titles and abstracts of the remaining articles, two researchers (LI and WK) independently reviewed the full text of 325 articles for inclusion and exclusion criteria. Any disagreements were resolved by consensus.

E. CRITERIA FOR INCLUSION AND EXCLUSION

Exclusion criteria were applied to limit the final selection of studies. To meet the eligibility requirements, we only included published articles that fulfilled the following criteria: (a) only English language publications; (b) experiments in humans; (c) studies using only the EEG technique; (d) experimental studies in healthy participants; and (e) content in peer-reviewed journals, conference publications, textbooks, and reference books.

Articles with the following features were excluded: (a) studies on brain diseases or neural disorders; (b) studies that used neuroimaging techniques other than EEG; (c) experimental studies in infants; (d) studies on pathological conditions; and (e) studies that investigated only the resting-task state without considering task-evoked activity. These exclusion criteria were applied because completely different global topological properties and brain architectural features are obtained for these key factors. Accordingly, an additional 273 studies were excluded from the current review. During the screening phase, we identified a large number of studies that focused on the human brain network during resting-state tasks.

To collect all relevant articles in the literature search, the reference lists of the candidate articles (n = 325) were reviewed, yielding five additional articles that met the inclusion criteria. The findings of the literature search and the selection process are summarized in a PRISMA diagram (Fig. 1). This aspect of the study was performed from October 2019 to February 2020.

F. DATA COLLECTION AND SUMMARY MEASURES

Relevant information from the included articles was extracted; this information is summarized in Supplementary Material A, which displays the node definition, edge definition, graph theory metrics, number of participants, domain, experiment, and primary findings, providing answers to RQ1 and RQ2.

G. DATA EXTRACTION AND SYNTHESIS

The selected articles were classified according to the following six domains: (1) fatigue; (2) workload; (3) working memory load; (4) exertion; (5) perception; and (6) motion.

H. QUALITY ASSESSMENT

Study quality was independently assessed by two researchers (LI and WK). Any disagreement between the authors was resolved by consensus. The Cochrane Collaboration method [61] was used to assess the risk of bias in each experiment in the selected studies. The Cochrane Collaboration method has six main domains: (1) random sequence generation; (2) allocation concealment; (3) blinding of participants and personnel; (4) blinding to outcome assessment; (5) incomplete outcome data; and (6) selective reporting. To assess the quality of the articles, the following judgments were used: low bias risk, unclear bias risk, or high bias risk.
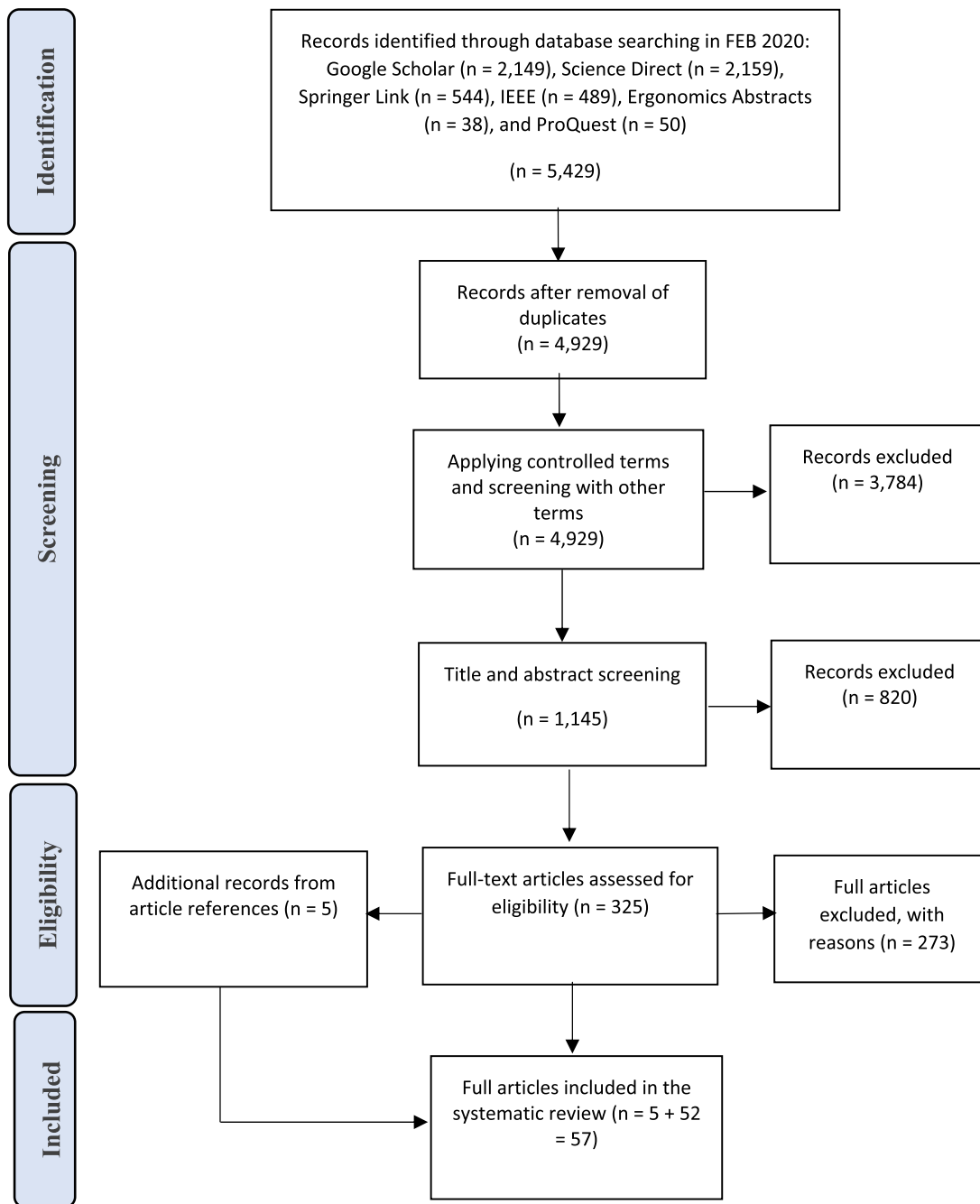
FIGURE 1. Flow diagram of the methodology and selection process used in this review, following the prisma guidelines [59].

III. THEORETICAL BACKGROUND

A. FUNCTIONAL CONNECTIVITY

Functional connectivity measures the statistical interdependence of physiological time series recorded in different brain regions [62]. Functional connectivity has been employed by several studies due to it being the best choice for analyzing functional neuroimaging data and developing computer simulation models [63]. Since the calculations of functional connectivity are highly dependent on brain activities over the time series, a high temporal resolution technique such as

EEG (< 1 ms) is the optimal choice to reflect the dynamic and rapid neural response [53]. Furthermore, EEG is a very promising method for connectivity analysis and causal inference, addressing RQ3. The statistical dependencies between pairs of regions are measured using different methods categorized into linear, nonlinear, and information-based techniques. These are sensitive to both linear and nonlinear statistical dependencies between two time series and can be used to assess causality. Table 2 provides an overview of the most established estimation methods for functional

TABLE 2. List of functional connectivity measurements, indicating: (1) whether it is a univariate or multivariate connectivity measure; (2) whether it is a directed or undirected connectivity method; (3) whether it is a time domain analysis, frequency domain analysis, or cross-frequency phase coupling; (4) whether it is a linear, nonlinear, or information-based technique; (5) sensitivity to the volume conduction [67]–[69].

Functional estimator	Univariate	Multivariate	Direct Causality based	In-direct	Time-domain	Frequency domain	Phase coupling	Linear	Non-linear	Info-based	Volume conduction sensitivity
Correlation	✔			✔	✔			✔			Highly sensitive
Cross correlation		✔	✔		✔			✔			Less sensitive
Magnitude squared coherence [70]	✔			✔		✔		✔			Highly sensitive
Phase locking value (PLV) [71]	✔			✔		✔	✔		✔		Highly sensitive
Phase lag index (PLI)	✔			✔		✔			✔		Less sensitive
Weighted phase lag index (wPLI) [72]	✔			✔		✔			✔		Less sensitive
Partial coherence		✔		✔		✔			✔		Robust
Mutual information [73]	✔			✔	✔					✔	Robust
Transfer entropy	✔		✔		✔				✔		Less sensitive
Generalized synchronization		✔		✔						✔	
Synchronization likelihood [74]	✔			✔					✔		Sensitive
Phase synchronization		✔		✔			✔		✔		Sensitive
Granger causality [75]		✔	✔		✔	✔		✔			Less sensitive
Directed transfer function (DTF) [67]		✔	✔			✔		✔			Sensitive
Imaginary part of the coherence [76]	✔			✔		✔		✔			Less sensitive
Partial directed coherence (PDC) [77]		✔	✔			✔		✔			Less sensitive

connectivity. It should be noted, however, that selecting the optimal estimation method is a challenging problem that is beyond the scope of this review article [64]–[66].

Univariate analysis should be used when analyzing the feature of a single signal from a particular neurophysiological technique, whereas multivariate analysis is typically applied when combining different neurophysiological techniques. A considerable body of evidence relies on linear methods; however, some researchers use nonlinear analysis methods to detect the nonlinear phenomena of the brain [78].

Other authors are opposed to using nonlinear methods since they are highly susceptible to noise [64].

B. THEORETICAL ASPECTS OF GRAPH THEORY ANALYSIS

Over the last two decades, the application of graph theory in the quantification of neurophysiological data has gained much attention in biology and neuroscience for the diagnosis of brain disorders such as epilepsy [79], [80], schizophrenia [12], Alzheimer's disease [62], rehabilitation after stroke [81], and other brain disorders (for a review, see

Vecchio *et al.* [9] and Farahani *et al.* [3]). Several subsequent works aimed to study the topological configuration of the brain in response to task modulation. Most of the studies presented herein primarily focused on cognitive neuroscience; hence, one of the aims of the current review was to shed light on the functional connectivity of the brain at work and during everyday tasks.

C. APPROACHES TO GRAPH THEORY

For a better understanding of network properties, the data are presented as a graph (G), which is a basic topographical representation consisting of a collection of V vertices (nodes) that are connected by edges (E) (links or connectors) (Fig. 2), where G = (V, E). To study the human brain network on a macroscopic scale, the nodes represent brain regions (i.e., EEG electrodes/sensors), whereas the edges represent statistical measures of association, including anatomical, functional, or effective connections [5], [46]. Graph edges include weighted direct, unweighted direct, weighted indirect, and unweighted indirect. A direct edge shows that the information flows in one direction only and that one node's activity depends on the other (i.e., causal influence); however, an indirect graph shows that information flows in both directions along edges that connect. The weight of the line between two nodes reflects the connectivity strength of the edge, which allows for discrimination between strong and weak connections. Weak connections can be removed by thresholding.
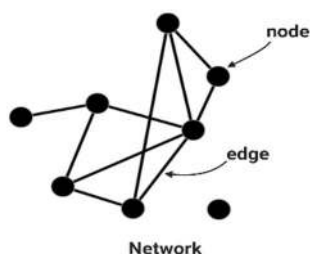

FIGURE 2. A small representation of a network containing eight nodes and ten edges. Modified from Newman [82].

1) PIPELINE STEPS FOR THE CONSTRUCTION OF A FUNCTIONAL BRAIN NETWORK BASED ON EEG DATA

The following eleven steps present the full pipeline for the construction of a functional brain network with graph theory of the EEG data using either the EEG sensor source method or space source method, which addresses RQ4. Previous studies have provided steps for either the sensor space method [40] or the source space method [53]. In the current study, we briefly describe the steps required for both methods focused on unweighted networks. We summarize all the steps of the pipeline, starting with the acquisition of EEG brain signals and ending with a statistical description of the brain network (Fig. 3). Our aim was to provide a simple stepwise method that can be used by non-expert researchers in the field.

a: DEFINE THE NODES OF THE BRAIN NETWORK

The nodes of the brain network represent the brain region. Defining the network nodes is a challenging step and significantly affects the outcome of the brain network analysis [83]. In EEG studies, nodes are defined using one of two approaches. The first approach is termed "sensor signals" or "individual channel" and relies on the predefined standard placement of the EEG electrodes (Fig. 3a) [84]–[86].

While this approach is simple, the volume conduction, which is the leading cause of reduced spatial resolution, may affect the accuracy of the functional connectivity estimates [69]. Thus, a second approach based on EEG source space connectivity has been proposed [53], [87], which can be achieved by subdividing the brain into different regions and selecting the regions-of-interest based on a parcellation scheme and individually segregated anatomical regions-of-interest (ROIs) from brain atlases [88], [89]. The source space is computed after the EEG signals are recorded (Fig. 3b), preprocessed, and epoched (Fig. 3c). The 3D electrode locations are then determined via the software acquisition system. To localize the brain source and reconstruct the time course, the inverse problem, which relies on dipole theory, must be solved [90], [91] by applying the following steps: (a) Obtain a head model by either using simple spherical head models or imaging a realistic head model by MRI (Fig. 3d). Realistic head models are usually preferable for an accurate calculation of the brain's electrical potentials and geometric characteristics; and (b) Estimate the source localization in the head model to determine the location of the dipole source and reconstruct the time course (Fig. 3e). Several algorithms are used for this purpose, including beamforming, low-resolution brain electromagnetic tomography (LORETA) [92], standardized LORETA (sLORETA) [93], exact LORETA (eLORETA), minimum norm estimate (MNE) [94], and weighted MNE (wMNE) algorithms. Subsequently, the source reconstructed time series is partitioned into individual ROIs from the brain (Fig. 3f) determined from functional atlases [95] to obtain a regional time series (Fig. 3g).

b: PREPROCESS THE EEG DATA

After high-quality EEG signals are recorded from the scalp surface, the continuous EEG time series data (Fig. 3b) must be preprocessed for segmentation, filtration, denoising, and artifact removal (Fig. 3c) [96]. EEG data are contaminated by different types of artifacts, which are categorized as physiological or non-physiological [97]–[100]. Various methods for data cleaning are discussed in [34], [101]. Then, specific time windows are extracted from the cleaned continuous EEG data "epochs."

c: DEFINE THE EDGES

The edges represent connections between different neurons or brain regions and exhibit various patterns of connectivity, including structural, functional, and effective
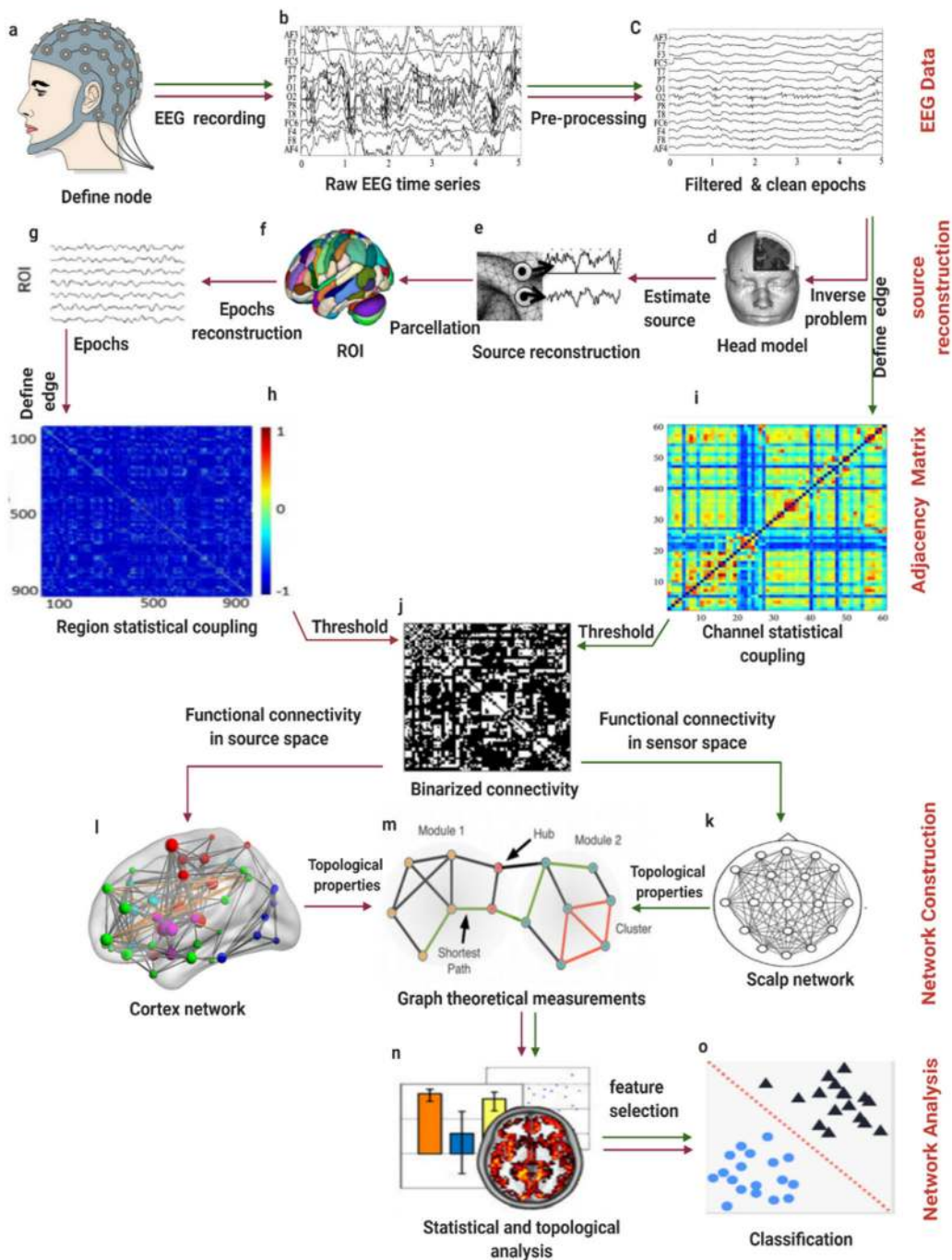
FIGURE 3. Schematic illustration of the pipeline for the construction of a functional brain network based on EEG data using graph theory. The green line defines the first approach, termed the "sensor signal" or "individual channels" method, while the red line defines the second approach, denoted as "EEG source connectivity." (a) Place the cap containing electrodes on the scalp. (b) Record the EEG time series. (c) Preprocess the data by cleaning, filtering, removing artifacts, and epoching. (d) Solve the inverse problem by first estimating or imaging the head model (method 2). (e) Reconstruct the electrical potential time source (method 2). (f) Parcel the source reconstructed epochs into the ROI (method 2). (g) Define the ROI for the epochs. (h) Develop the connectivity matrix for the selected ROI. (i) Develop the connectivity matrix for the selected EEG channels (method 1). (j) Apply the threshold value(s) to binarize the connectivity matrix (methods 1 & 2). (k) Construct the scalp functional brain network between EEG electrodes. (l) Construct the cortex functional brain network within the ROI. (m) Apply the network topological properties to calculate graph theory measurements. (n) Apply statistical analysis methods. (o) Classify different states, if needed [157].

connectivity [102]. In functional connectivity, the edges represent the time series correlation between two different nodes (Fig. 3c) or regions (Fig. 3g). The edge is categorized as either direct or indirect with or without weights. Weights

provide more information about the relationship between node pairs.

d: COMPUTE THE CONNECTIVITY MATRIX (A)

The connectivity matrix is known as the adjacency matrix and contains information regarding the associations among connectivity patterns. The connectivity is described by an N × N symmetric matrix, in which the rows (i) and columns (j) denote nodes, and matrix entries (aij) denote edges. There are two types of metrics: one is based on channels (Fig. 3i) and the other is based on the brain region (current densities for each brain region pair) (Fig. 3h).

e: CONVERT THE CONNECTIVITY MATRIX INTO A BINARIZED MATRIX

Matrix binarization is performed to convert the adjacent matrix to an unweighted matrix (Fig. 3j). For matrix binarization, a threshold value is calculated for each element. If the correlation measures for each pair exceed the threshold, value edges are added between node pairs (otherwise no edge exists) [37].

f: CHOOSE A THRESHOLD VALUE

The optimal threshold value is an open question in the literature. Thresholding helps to simplify the complexity of the brain network calculations by eliminating weak, noisy, and insignificant edges from the network. Moreover, thresholding facilitates the definition of the null model for statistical comparison [4], [40], [80]. Selection of the threshold value significantly affects the network topology properties and the ability to detect differences among groups, ages, and genders. Selecting an inappropriate threshold method creates instability and increases the bias; therefore, careful selection is crucial. A key factor is to select a method capable of controlling and minimizing the occurrence of type I errors (i.e., false-positives) [103].

Some criteria for appropriate threshold selection are reported in [103]–[105]. A variety of thresholding methods are available, including fixed threshold, fixed average degree, and fixed edge density (for a detailed review, see [104], [106]). However, none of these methods are free from bias. To perform statistical inference on connectome data, some researchers have suggested to "independently test the hypothesis of interest at each discrete density along the curve" [107]. In contrast, others have recommended more sophisticated methods, such as false discovery rate (FDR) error metric, network-based statistics (NBS) [88], and subnetwork-based analysis[88], [108], [109]. The threshold-free network-based method provides statistically significant thresholding values [108]. Drakesmith [110] proposed a multi-threshold permutation correction approach for improving sensitivity to substantial group effects with minimal *a priori* assumptions. The minimum spanning tree avoids methodological biases when comparing networks [111] and helps to rectify thresholding issues [112]. A novel methodology, namely the minimum connected component (MCC), has been proposed by Vijayalakshmi *et al.* [113], which overcomes the threshold issues.

g: ESTIMATE THE FUNCTIONAL CONNECTIVITY MEASUREMENT

A comparison between the methods for functional connectivity estimates are summarized in Table 2. A comprehensive review of these articles is provided in [44], [114]. Unfortunately, there is no optimal method to universally assess the functional connectivity [115], [116].

The following factors should be considered when choosing the functional connectivity estimator: (1) the definition of the underlying hypothesis that will be studied [44]; (2) the nature of coupling linear interdependencies, nonlinear interdependencies, or information-based techniques [116], [117]; (3) the time domain- or frequency domain dependence of the estimator that is originally based on the neuroimaging technique being selected in the study [44]; (4) the frequency specificity of the interaction (broad vs. narrowband); (5) direct (i.e., causal interaction) or indirect type of measurement [65]; (6) model-based or data-driven techniques [65]; (7) stationary or quasi-stationary brain signals [44]; (8) bivariate or multivariate modeling consideration [114]; (9) source or sensor electrode connectivity; and (10) the sensitivity to volume conduction phenomenon [69], [118].

In general, the EEG signals are best expressed based on frequency domain characteristics to distinguish between neural and artifact signals; thus, methods for frequency-based functional estimators are particularly attractive [119]. Furthermore, the extraction of several different frequencies of brain signals is possible with the frequency domain method. Pereda *et al.* [78] support the use of multivariate analysis methods, but nonlinear methods have also been used since they are more sensitive to the detection of nonlinear coupling in EEG signals [116], [120], [121]. Several MATLAB-based toolboxes are available for estimating the source or functional connectivity and analyzing the network measurements, as summarized in [53].

h: CONSTRUCT THE NETWORK

Mathematically, a network is a matrix [9], and the binarized matrix is converted into a sparsely connected graph, represented as a scalp graph (Fig. 3k) or cortex network (Fig. 3l).

i: ANALYZE THE DATA USING GRAPH THEORY

Different graph theory metrics are used to quantify network structures by analyzing the topological properties of the network (Fig. 3m). Graph theory is used to extract features from the functional connectivity network. Different toolkits have been developed to visualize and analyze topological properties, as summarized by Xia *et al.* [122] and Hassan and Wendling [53]. In the following section, we present a detailed description of the measures used to detect aspects of functional integration and segregation for unweighted networks.

j: APPLY STATISTICS

Statistical methods are applied to compare graph theory metrics and topological network properties and assess their statistical significance (Fig. 3n). This step is usually performed by either comparing two different states (alert vs. drowsy), conditions (movement vs. rest), populations (healthy vs. diseased), or genders (males vs. females) or by comparing results with a theoretical reference network [128]. Meanwhile, there is no predefined way to assess the statistical variability. The application of confidence intervals is essential for measuring the significance of the obtained results and proving the reliability of graph analysis of functional brain networks. Other methods for statistical inference include nonparametric statistics, permutational statistics, and bootstrapping, which are the most appropriate for the nature of EEG data [2]. The aforementioned statistical methods failed to address the graph topology between the massive edge features, leading researchers to develop a novel pathway for investigating the phenotype of connectome features [82]. An automatic k-partite graph detection (KPGD) algorithm succeeded in identifying the k-partite subgraphs in complex networks [124]. Hierarchical Bayesian Gaussian graphical models have been recently proposed to provide robust brain network estimation [125], [126].

k: CLASSIFY THE CONDITIONS

Several methods have been employed to classify different brain states (Fig. 3O). Functional connectivity estimates have been used to classify fatigue and non-fatigue conditions [127], whereas hand movements have been classified based on network node strength [128]. Other classification algorithms, such as artificial neural networks [129] and support vector machines [130], [131], have been used to classify mental workload and mental fatigue with connectivity features.

D. GRAPH THEORY MEASURES AND NETWORK TOPOLOGY PROPERTIES

Network measures are calculated for the quantitative investigation of network properties. Table 3 presents a short non-mathematical description of the commonly used network measures categorized into global (graph) and local (nodal) measures. Global measures include the characteristic path length (PL), clustering coefficient (CC), small-worldness (σ), global efficiency (Eglobal), local efficiency (Elocal), transitivity (T), network density, assortativity (r), and modularity (Q); whereas, nodal measures include nodal centrality, node degree, hubs, degree distribution, degree correlation, betweenness, eigenvalue centrality, eccentricity centrality, closeness centrality, nodal efficiency, and motifs. The provided definitions are limited to unweighted graphs. Detailed descriptions of these network measures and their interpretations are provided in several studies [4], [132]–[135]. Furthermore, reviews on the application of graph theory in neuroscience can be found in many previous works [102], [136], [137]. Several software packages

are available for the identification and characterization of network measurements, including BCT [5], EEG-Net [138], [139], and BrainNet Viewer [122].

1) NETWORK TYPES

There are four types of networks: regular, well-ordered, or lattice-like networks; random networks; small-world networks; and scale-free networks (Fig. 4) [140]. These different networks are distinguished based on the number of local segregation events (represented through CC) and the global integration between nodes (represented through PL). Regular networks have a high CC and a long PL, indicating that the network is robust but inefficient at transferring information. In contrast, random networks have a small CC and a short PL, indicating that the network is efficient at transferring information but is not robust.
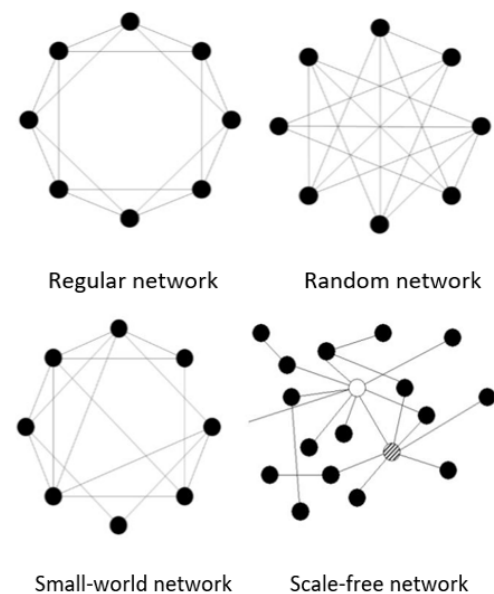
FIGURE 4. Four types of networks (in the scale-free network, the white and striped nodes represent network hubs) [136], [149].

A small-world network is intermediate between regular and random networks and has a short PL similar to a random network, and a higher CC than a regular network [141]. Small-world networks are considered near-optimal networks in terms of segregation, integration, cost, and performance [62], [74]. A scale-free network is unique due to its extremely short path length [136], [158], [159], and strikes a balance between global and local communications [160] with a power-law degree distribution. Other network classifications have been proposed by Kaiser [102], which are based on topological and spatial organization.

IV. RESULTS
A. STUDY CHARACTERISTICS

A total of 57 articles met the selection criteria. Just under half of the selected articles (44%; n = 25) were published from

TABLE 3. Typical Network measures.

Global measurement	
Characteristic path length (PL)	is the average of the shortest path lengths over all possible nodes in the network [141], [142]. It is used to measure the functional integration of brain regions and provides information regarding the global communication. A low PL shows greater functional integration among brain regions and is an indication to the ease of information flow.
Global efficiency (Eglobal)	is the inverse of the average shortest path length and is used to quantify the overall efficiency of information transfer across the whole network (i.e., global information processing) [132]. A higher Eglobal value indicates a faster parallel transfer of information in a network [133] and a superior integration of information [143].
Clustering coefficient (CC)	is the ratio of the number of existing edges between adjacent nodes to all possible connected edges [83], [102]. It is used to measure the functional segregation of brain regions and provides information regarding the local efficiency. A higher clustering coefficient corresponds to more robust and efficient local interactions (i.e., a more segregated network).
Small-worldness (σ)	is the ratio of the normalized CC (denoted as γ) to the normalized PL [144], [145] and quantifies how close a network is to a small world [146], indicating that most nodes can be reached from any other node in a small number of steps [46].
Transitivity (T)	is the number of triangles in the matrix [5].
Network density (D)	is the actual number of connections within the model divided by its maximal capacity. Density ranges from 0 to 1; the sparser a graph, the lower its value [147].
Assortativity	is the tendency of nodes to link to other nodes with similar numbers of edges [148].
Modularity (Q)	Modules are large subgraphs with nodes that are more connected to each other than the rest of network, as defined by Stam [149]. Modularity is a measure of the network structure according to the statistical arrangement of edges [150].
Nodal (local) measurement	
Local efficiency (Elocal)	is the average efficiency of all pairs of nodes, indicating the efficiency of information transfer among the first neighbors of a given node [136].
Nodal centrality	reflects the relative importance of a node to the network. There are several metrics for measuring nodal centrality, including degree centrality, betweenness centrality, eigenvalue centrality, closeness centrality, and node efficiency.
Degree centrality (K)	is the number of edges that connects one node with all other nodes, quantifying the importance of the node in the brain functional network. A higher degree centrality indicates a more central node. The incoming node connections are referred to as "afferent," while the outgoing connections are referred to as "efferent" [102]. A node with a high degree of centrality is referred to as a "hub" [40], [151].
Hub	is a node with more edges than any other node [102] and indicates the important brain regions that interact with other regions [40]. Provincial hubs are those connected to other nodes in the same module, whereas connector hubs are connected to nodes in other modules [152].
Degree distribution P(k)	is the probability distribution of the degrees of all network nodes and provides information regarding the network structure.
Degree correlation	shows whether the degree of a node is influenced by another node to which it is connected [136].
Betweenness	is the tendency of a single node to be more central than all other nodes in the graph, as defined by Unnithan et al. [153]. It is a measure of the extent to which a node lies on paths between other nodes.
Eigenvalue centrality	measures the ease of accessibility of a node (i) to other nodes [154].
Closeness centrality	shows the closeness of a node in the network to all other nodes [154]. The more central a node, the closer it is to all other nodes [155].
Nodal efficiency (Enodal)	measures the ability of a node to propagate information to the other nodes in a network, as defined by Wang et al. [137].
Motif (M)	is a simple subgraph consisting of a small number of nodes connected in a specific way, as defined by Stam and Reijneveld [136].
Network cost	is the ratio of the existing number of edges to the number of all possible edges in the network, as defined by Wang et al. [137]. Network cost is also referred to as network density. A costly network has many edges with high weights [156]. A network with high Eglobal and Elocal values is considered an economic small-world network [134], [141].

2006 to 2016, whereas over half were published within the last three years (56%; $n = 32$). Thus, this review demonstrates an increasing trend in brain function studies using brain connectivity techniques and graph theory metrics (Fig. 5). We expect the number of future studies to increase dramatically over the next several years.
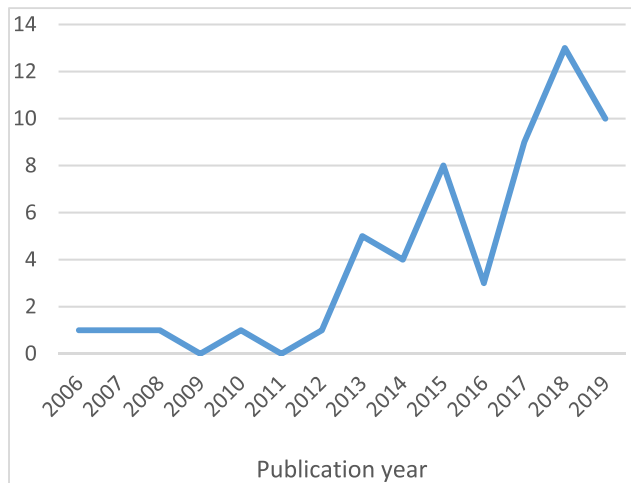
FIGURE 5. Scatter plot of the publications per year of graph theory studies relevant to neuroergonomics based on EEG data.

B. QUALITY ASSESSMENT

To evaluate the strength of evidence in these studies, we applied the standards of the Agency for Healthcare Research and Quality [161]. Studies of good quality were judged to have a low risk of bias; studies of fair quality were judged to have two unclear criteria; and studies of low quality were judged to have a high risk of bias. The overall quality of the studies was categorized as good, fair, or low if the number of low-risk domains was ≥ 4, = 3, or ≤ 2, respectively.

Of the 57 studies included in this systematic review, n = 18 were classified as good-quality, n = 7 were classified as fair-quality, and n = 32 were classified as low-quality (Fig. 6).

This finding can be attributed to the fact that most studies neglect to describe random sequence generation and allocation concealment. Moreover, an unclear bias results from unclear selective reporting of the data and attrition; thus, the level of evidence in the included studies is low.

The present review analyzed the performance in different domains and found that the majority of the reviewed articles focused on fatigue followed by workload assessment.

Overall, the evidence indicates that cognitive functions (80%) are more frequently addressed than motor processing (20%). Techniques for estimating functional connectivity, including PLV [71], PDC [77], and PLI, exhibited the greatest potential impact (40%) (Fig. 7). Numerous studies (n = 9) employed the PLV technique since it overcomes the limitations involved in using traditional coherence methods and calculates the linear correlation among EEG signals [71]. The PLV technique is followed by PDC in frequency of use, since this technique allows assessment of the statistical interdependence of EEG signals in the frequency domain [77], [162]. Further, Stam *et al.* [62] suggested the use of PLI for non-stationary EEG data. PLI is less sensitive to volume conduction than other connectivity measures [72], [163], and has a lower impact on gait-phase-locked artifacts [164]. The use of a weighted network

leads to a rich topological brain organization; however, many of the selected studies (n = 48) used an unweighted network, known as a "binarized network," whereas only a few (n = 9) applied a weighted network. The CC and PL are the most frequently used graph theory metrics (average, normalized, or weighted) (n = 33 and 26, respectively) (Fig. 8). We further found that approximately 79% of studies analyzed indirect networks, while 21% assessed direct networks. Our findings are consistent with the FMRI study reported by Bullmore and Sporns [4]. Both the CC and PL are helpful in the evaluation of small-world organization [156]. The CC is useful for quantifying functional segregation in the brain, whereas the PL is useful for quantifying network integration. Furthermore, the calculation of both Eglobal and Elocal depends on these two metrics. The construction of the connectivity matrix and calculations of the matrices can be accomplished with the aid of different software programs. A commonly used toolbox in the selected articles (n = 22) is BCT [5], which has a large number of topological metrics and is an open-source MATLAB toolbox.

A critical aspect of any EEG functional connectivity network is the selection of the number of nodes, which are represented by the recording electrode channel number. Two recommendations for this selection were found in the literature. A denser electrode distribution results in a high clustering coefficient and may cover more areas for future findings. A large number of electrodes (i.e., ≥ 64 channels) is recommended for the EEG source connectivity method [53], [147], [165], [166].

Furthermore, a large number of electrodes increases the accuracy of electrical source estimation [167] and signal preprocessing [47]. In contrast, García-Prieto *et al.* [168], Li *et al.* [169], and Wang *et al.* [170] recommend fewer than 32 electrodes, demonstrating that a small number is adequate to cover the ROI and obtain reliable information. A small number is also suggested by Luck [33], indicating that the use of 16–32 active electrodes is better for monitoring brain activity. The electrode numbers used in previous publications are summarized in Table 4. According to our analysis, 20 studies followed the first recommended condition, with ≥ 64 electrodes, 31 studies followed the second strategy (≤ 32 electrodes), and the remaining studies (n = 6) used between 32 and 64 channels.

The demographic distribution of the studies included healthy male and female participants (Fig. 9). Of these, 21 studies used males only, whereas none of the studies used only females. The majority of studies had a higher number of males than females (n = 16). The remaining studies (n = 9) did not precisely describe the number of participants by gender, as presented by the green bars (Fig. 9).

V. DISCUSSION

This section describes the major findings of the reviewed studies. Considerable changes in the functional brain network configuration have been demonstrated in different cognitive and physical states. This section also provides insight into
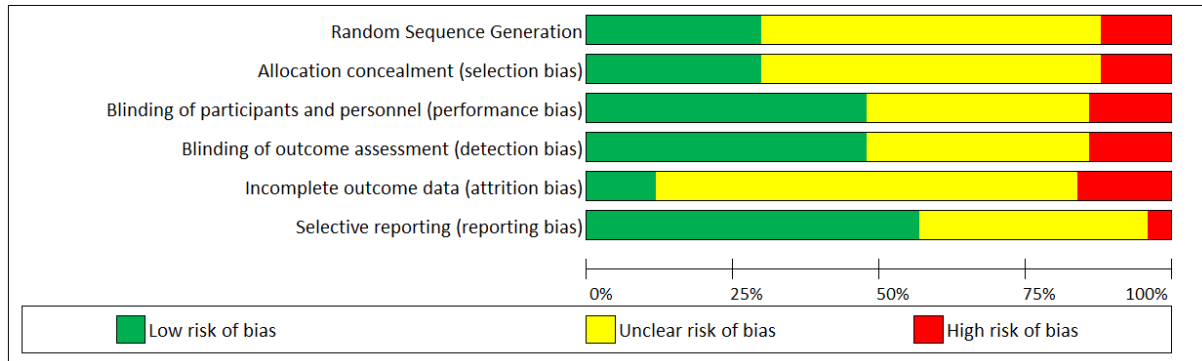
FIGURE 6. Assessment of the risk of bias using the Cochrane Collaboration tool.
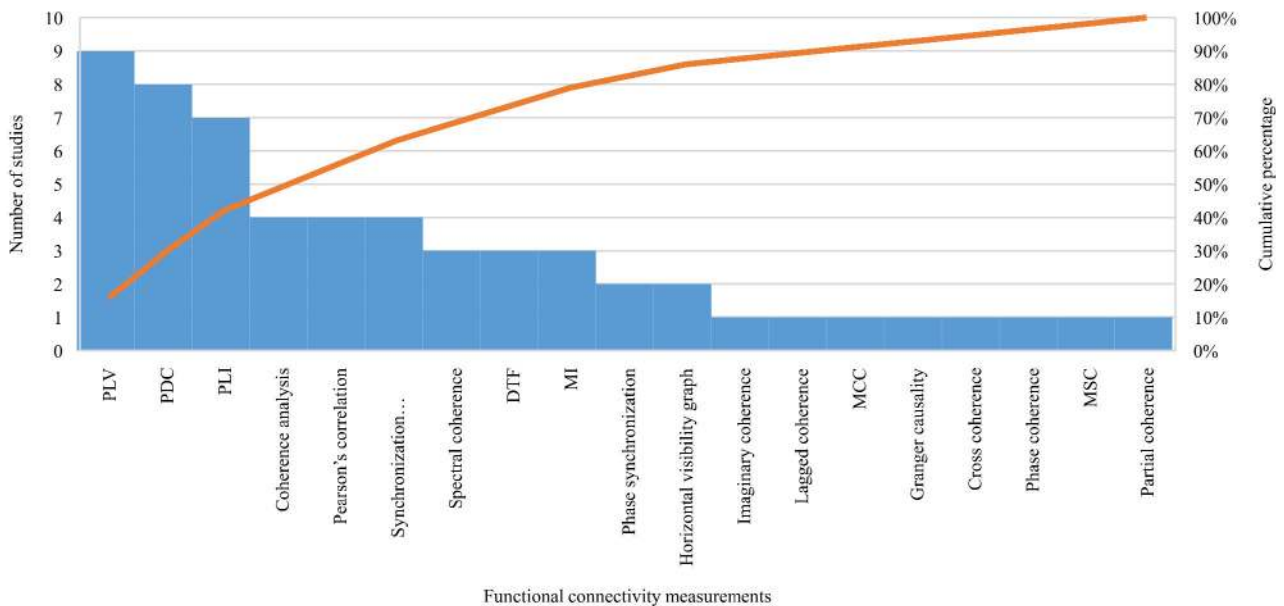

FIGURE 7. Pareto chart of methods for estimating functional connectivity (phase-locking value [PLV], partial directed coherence [PDC], phase lag index [PLI], directed transfer function (DTF), mutual information [MI], minimum connected component [MCC], and magnitude square coherence [MSC]).

TABLE 4. Number of studies for each range of recording electrode number.

Number of recording electrodes	Studies (n)
≥ 64	20
$32-64$	6
≤ 32	31

the application of graph theory in the study of cognitive and motor processing, in line with RQ1, RQ2, and RQ5.

Application of Graph Theory in Functional Brain Network Analysis: This subsection is grouped into six main domains: fatigue, workload, working memory, exertion, perception, and motor processing. There is some degree of overlap in the cognitive processes. For instance, the cognitive workload is

directly related to the allocation of resources to the working memory and its association with attentional processes, which can be substantially affected by mental fatigue [171].

A. CONNECTIVITY STUDIES ON FATIGUE

Mental fatigue is a complex psychobiological state in which a high level of cognitive and motor activity is required during a prolonged task [172]–[174]. In general, fatigue diminishes human performance by slowing the response time, increasing the error rate, increasing drowsiness, and causing musculoskeletal disorders. Previous studies have addressed the underlying neural mechanism of mental fatigue in realistic applications [175]. In particular, the effect of mental fatigue on vehicle driving and piloting performance has gained much attention in the neuroergonomics literature [172], [174]–[180]. The PSDs of the alpha and theta bands have been shown to
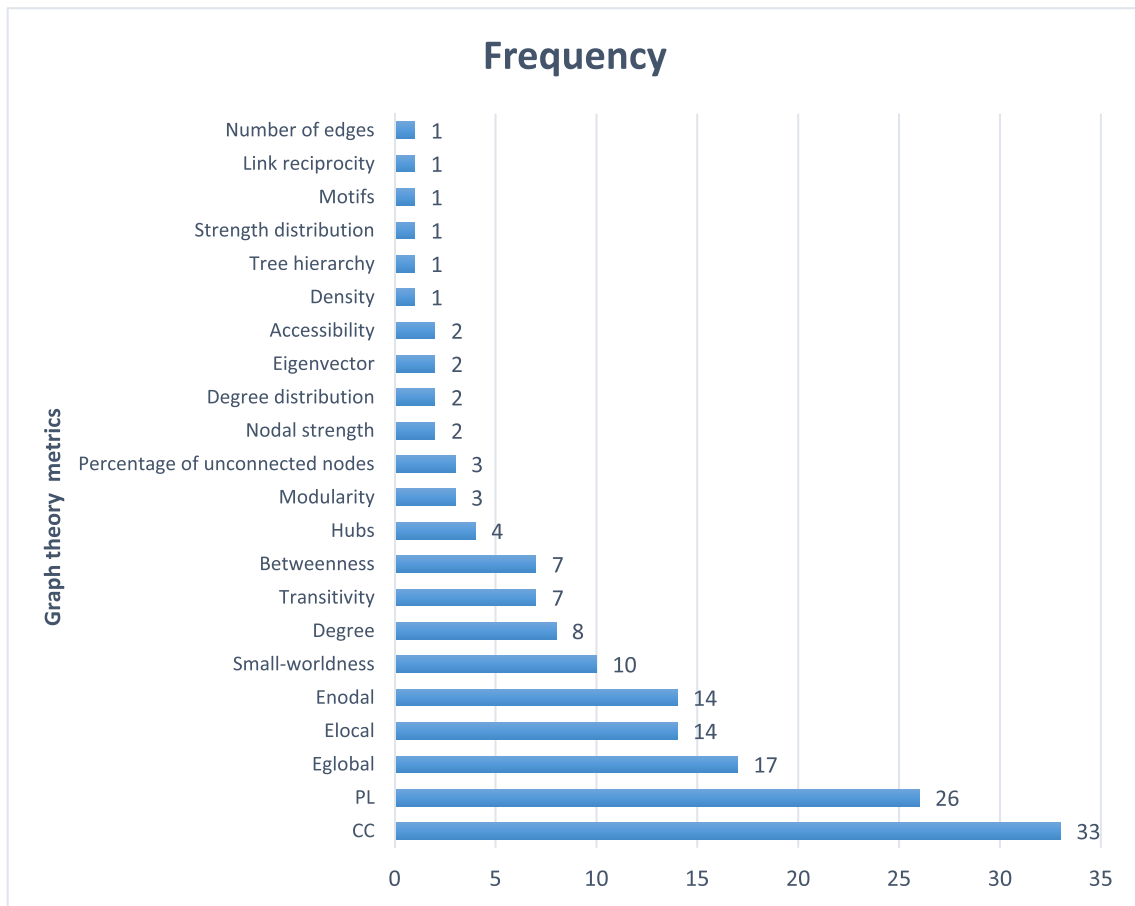
FIGURE 8. Frequency of graph theory metrics.
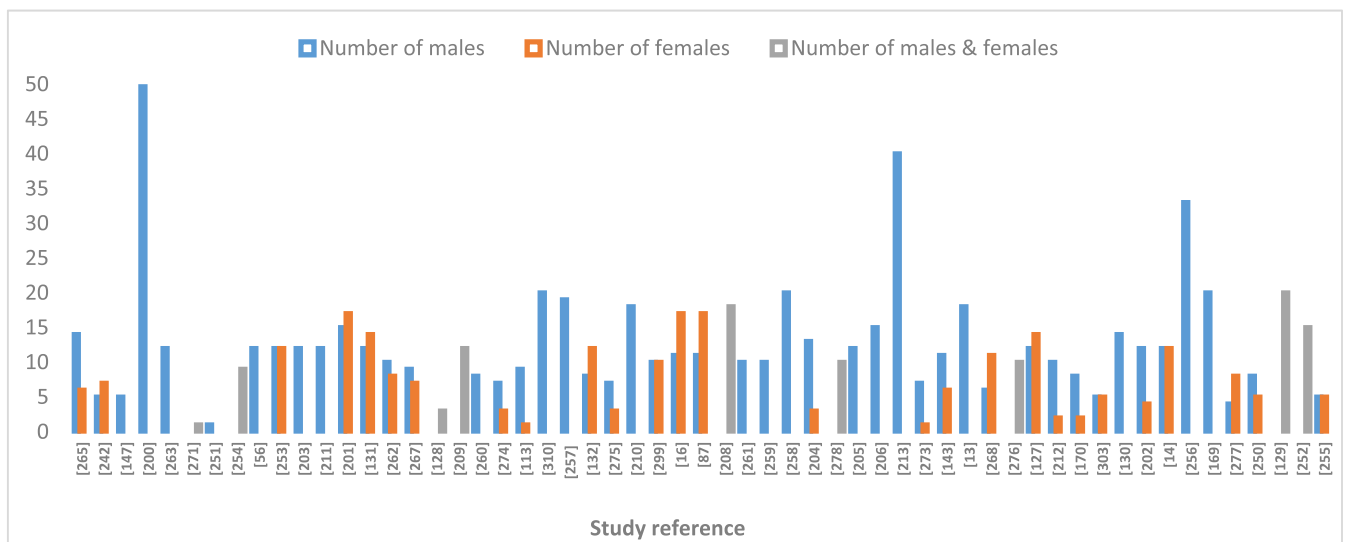
FIGURE 9. Demographic distribution of the studies that included healthy male and female participants.

be robust indices of neural changes related to fatigue [175], [181]–[197]. A significant increase in PSD for both frequency bands is primarily associated with mental fatigue in the frontal cortex, medial prefrontal cortex, fronto-central, occipital, and parietal brain regions [181]–[183], [185]–[187], [191], [195], [196], [198], [199]. Recent studies

in cognitive neuroscience have explored the interactions among brain regions after the performance of fatiguing tasks. The functional connectivity of the frontal, central, and parietal brain is strongly correlated with mental fatigue [200]. The middle frontal gyrus and several motor areas are connected during tasks that require sustained attention [131]. Different patterns of connectivity between the right and left hemispheres in sensorimotor areas have also been demonstrated during a state of fatigue [201], similar to the findings of Liu *et al.* [200] in different brain regions.

In addition, some studies have observed denser functional connectivity during post-fatigued tasks in comparison with pre-fatigued tasks, indicating that the human brain exhibits stronger coupling during fatigue to maintain information transmission until the required task is accomplished [56], [202]–[206]. A higher phase coherence for the alpha and theta bands [205] and a higher PLI for the delta band [206] have been demonstrated during drowsiness in comparison with a state of alertness, indicating a lower degree of asymmetry in the phase difference.

However, there are also contradictions in the literature; for example, it has been reported that the functional connectivity of the alpha band in the parietal-to-frontal region [200] and of the alpha and beta bands in the frontal-to-parietal region [130] become weaker as mental fatigue increases. Furthermore, it has been shown that fronto-occipital coherence values in the alpha range decrease during the shift from alertness to drowsiness [207]. Results of the aforementioned studies support the notion that cortical-to-cortical functional coupling—mainly in the frontal, central, and parietal lobes of the cerebral cortex—can characterize the brain during mental fatigue over short time scales.

Changes in the topological properties of the brain network reflect human mental states. For instance, an increase in the maximum eigenvalue of the alpha band reflects a deterioration of performance in humans [208]. Poor attention during a mental task is characterized by a decreased PL in the delta and theta bands [209] and an increased CC [169], [210], [211]. The results reveal that fatigue increases Elocal but reduces Eglobal, indicating that the resources of the brain may be reorganized and the interactions between regions may be inhibited. This trend reflects a decrease in the ability of the human brain to integrate information during fatigue [209] and leads to a small-world configuration [169], [204], [210]. A lack of awareness as a result of mental fatigue has been demonstrated by an increase in the CC and in the Eglobal value of the sub-band (36–44 Hz) [212].

An increase in the degree of centrality in the right parietal brain regio in the delta rhythm [170], [202], and in all frequency bands [56], [208] indicates good connectivity among nodes with a reduction in alertness. However, contrasting results have also been demonstrated, such as an increase in the percentage of unconnected nodes, indicating breakdowns in connections during the shift from alertness to drowsiness [209]. Moreover, some studies have reported decreases in the CC, average degree, and network density, and an increase in the PL after a fatiguing task [130], [132], [201], [213], [214].

An increase in the betweenness centrality in the frontal cortex has also been observed during fatigue [132]. A mid-task break (rest) is an effective way to improve the efficiency of the brain network, thereby mitigating the occurrence of fatigue [132], [215], as evidenced by a slight increase in both the CC and PL after a rest between sessions.

Since human performance declines over time, a positive correlation between the time spent on a task and network metrics (primarily the node degree, CC, and PL) has been observed [170], [213]. However, the results of some studies contradict these findings [15], [127], [131], where an increased time spent on a task results in a linear reduction in the network topology. An increased PL and a decreased small-worldness result in a less optimal brain network as the time spent on tasks increases [127]. Furthermore, a prolonged time spent on tasks reduces the network betweenness in the central and left frontal regions but increases the network betweenness in the right parietal region.

B. CONNECTIVITY STUDIES OF MENTAL WORKLOAD

As discussed by Young *et al.* [216], the mental workload is one of the most widely invoked concepts in the field of ergonomics [217]–[220], and as a multidimensional construct, can be defined in terms of the resources available to meet task demands [221]–[231]. The mental workload assessment based on neuronal data has been of great interest in neuroergonomics studies (for a review, see Borghini *et al.* [172]). The neuro-indices of cognitive workload [232], including EEG-based workload, have been discussed in the context of human-computer interactions [233] and a virtual driving environment [234].

The PSDs of the frontal theta, occipital theta, and parietal alpha have been demonstrated as a powerful assessment tool for discriminating the state of mental workload. A reduced parietal alpha PSD and an increased frontal theta PSD have been observed as task difficulty increases [172], [177], [235]–[248]; however, other studies have shown inconsistent results [249].

Discrimination between different levels of difficulty is reflected in the functional connectivity of the brain network, mainly in the prefrontal and parieto-occipital regions. Furthermore, a decrease in functional connectivity has been shown to indicate a reduction in human accuracy during difficult tasks [250]. A lower PLV has been demonstrated in parieto-occipital regions during highly difficult tasks in comparison with tasks of lower difficulty levels [251]. The weighted PLI value for the alpha band in all brain regions has been shown to decrease under a high cognitive workload, whereas an increase is evident in the coupling of the theta band during a physical task [252]. Dimitrakopoulos *et al.* [87] found that the majority of changes related to the difficulty of cognitive tasks occur in frontal theta and beta activity, based on the features obtained from analysis of functional connectivity.

Discrimination between cognitive difficulty levels and the detection of cognitive impairment [113] can be performed by analyzing graph measurements [253]. Patterns vary between high and low cognitive or physical workloads. Furthermore, results may vary from the left to the right hemisphere [254]. The significance of these classifications can help to characterize dangerous situations in the workplace [255].

The Eglobal and Elocal values have a significant impact on workload level, where increases in the alpha and beta Elocal activities are associated with elevated workload levels. The Eglobal beta pattern shows a unique trend [256]. Huang *et al.* [257] observed a decrease in the Elocal of the theta band and an increase in the Elocal of the beta band during play. Furthermore, a lower Eglobal in the beta band and a higher Eglobal in the theta band were observed when comparing the network organization with that of the resting state. During the transition from subitizing to retrieval during a mathematical processing task, an increase in the Elocal and Eglobal values was observed for the delta, theta, and alpha bands, mainly in the fronto-parietal regions [253]. Particularly, increased effort results in an increased Eglobal, yielding a more integrated network and a higher transfer rate of parallel information. A reduction in the segregation process is reflected by a reduction in the CC and modularity. Zhang *et al.* [258] reported less modularity, less clustering, a high Eglobal, a low Elocal, and a greater physical synchronization distance in the beta and lower gamma bands during difficult mental tasks. Moreover, a reduction in the alpha and beta CC, with a significant increase in the alpha strength in the central and parietal brain, has been demonstrated for high workload levels [129], [259]. These results demonstrate that during a high workload, the human brain network has a small-world network topology (less clustered and more globally efficient) [260], [261]. Interestingly, Klados *et al.* [253] observed that an optimal small-world organization is evident during both mathematical tasks and rest. Vijayalakshmi *et al.* [113] demonstrated a high degree of interactions among different electrodes and increased functional brain segregation of the beta bands [14].

Local properties appear to be more crucial than global properties during cognitive processing. For instance, the local CC is much greater than the global CC during a target recognition task [262]. Moreover, the node strength exhibits a higher value in the frontal lobe and left hemisphere than that in global activity [253]. Furthermore, Enodal increases in motor executive areas during finger-tapping tasks [263].

C. CONNECTIVITY STUDIES OF WORKING MEMORY

Working memory is related to the process of storing and processing information. Many situations in the workplace require the manipulation and recall of information for decision-making and problem-solving. The ability to recall and store information is negatively impacted by fatigue, stress, and workload, which in turn affects attention levels, situational awareness, and learning performance. Training, practicing, and learning reduce the workload on short-term

memory by storing necessary information in long-term memory. Thus, cognitive brain function can be improved through working memory training, as evidenced in topological network changes, mainly in the beta band. An inverted U-shaped curve is observed for the CC and small-worldness, whereas the PL exhibits a contradictory pattern [160]. Taya *et al.* demonstrated that the global network properties for the high-frequency bands increase during training, whereas the local properties and small-worldness reduce [13]. Interestingly, the node betweenness exhibits a change in the frontal and temporal regions during training. However, Langer *et al.* [264] found an increase in the theta CC and a reduction in the theta PL length during training-induced working memory. Therefore, training improves the local network connectedness and global efficiency of transferred information.

A greater phase coherence of the theta band in the frontal and posterior parietal regions is evident when comparing a well-trained, memorized sequence experiment with a novel task [242]. The brain organization of well-educated participants is less organized than that of less-educated participants during a working memory task [265]. Furthermore, a large scale network reconfiguration was found in the coherence theta band after training [264]. Although the connectome approach has been applied in limited studies to understand the brain organization underlying cognitive training, the approach is very promising for the characterization of cognitive functions.

Studies on working memory have primarily focused on the functional interaction between alpha and theta bands in the parietal, frontal, and parieto-occipital brain regions. Klimesch [266] reported that a long-term memory leads to desynchronization of the alpha band, whereas a short-term memory leads to synchronization in the theta band. Changes in phase synchrony of the theta and alpha bands in the frontal and parieto-occipital regions were found with different workload memory levels [267].

Different topological properties have been observed in all frequency bands during encoding, storage, and retravel [268]. Working memory tasks require a high degree of cognitive effort, resulting in lower clustering and modular configurations but a higher Eglobal for the alpha, beta, and gamma bands [269]. When comparing a working memory task with a resting task, a high degree of functional integration in the theta band [250] and low functional segregation in the alpha band have been observed [16]. Thus, a small-world topology is evident with respect to the storage and retrieval of memories in all frequency bands [268].

D. CONNECTIVITY STUDIES OF MOTION

Motion is essential for everyday tasks since "*human action is orchestrated by mind (and brain) and body interactions*" [270]. The contralateral somatosensory, ipsilateral somatosensory, and motor areas of the brain are strongly related to the function of motor processing. Before movement occurs, there is a transfer of information from the

contra- to the ipsilateral hemispheres, whereas the opposite pattern occurs after movement [76]. The increase in network edges during the preparation for movement demonstrates the need for a higher degree of information exchange in order to execute movement-related tasks [147]. Moreover, decreased accessibility and increased centrality have been observed during the preparation and execution of finger movement tasks.

Different patterns of coupling are observed for different intervention strategies. Particularly, different intensity levels during a cycling task generate different patterns of brain connectivity in the alpha and beta bands of the prefrontal motor and central areas [271]. Furthermore, an increase in synchronization has been observed in the parietal and occipital lobes after physically and visually fatiguing tasks [203]. Increased mutual information values for the beta band have been observed during a finger-tapping task, reflecting an increase in the flow of information [263]. Lastly, a strong interaction between the sensorimotor and prefrontal areas has been shown to occur during the transition period from the resting state to the hand movement [272].

Local network properties have been considered during left- and right-hand movement tasks in order to classify different movements [273]. Ghosh *et al.* [128] showed that the node strength could be applied to the classification of hand movements without the need for a classifier. The Enodal value for the left sensory and bilateral primary motor cortices increases during motion-related tasks but decreases in posterior parietal areas [263]. Furthermore, researchers have observed an increase in the functional connectivity of the motor region during arm movements, as well as reduced node accessibility and increased node centrality [274], [275]. Two years later, the same research group [276] found that arm movements significantly reduced network connectivity, primarily in the alpha and beta bands, and reduced the weighted PL only during movement of the left arm. However, neither the CC nor the small-worldness exhibited any significant changes. Jin *et al.* [263] observed the economy of small-worldness in alpha and beta band networks during finger movement and resting tasks. The medial premotor and bilateral prefrontal cortex for the gamma and beta bands appear to have greater connectivity and a higher CC, but a shorter PL during motor tasks [105]. Significant changes in the hubs of the lower beta and gamma bands in the superior parietal somatosensory cortex have been shown to characterize visuomotor associations [277]. A comparison between the node degree of spectral coherence and that of imaginary coherence in the beta band during a motor task showed that the spectral coherence network outperforms the imaginary coherence network in the contralateral motor cortex [278].

E. CONNECTIVITY STUDIES OF PHYSICAL EXERTION
Exertion is directly related to workload [279] and reflects the fatigue, strain, intensity of effort, and discomfort that a subject may face during physical exercise [280]. An increase in partial theta coherence has been observed in the frontal region during working memory tasks associated with physical exertion. An interesting U-shaped pattern was initially observed in the CC, where the CC of the theta band increased during both physical exertion tasks and mental tasks and decreased significantly when the tasks became more difficult [250]. The study limited its investigation to the frontal brain region; however, future studies should investigate the topological properties across the entire brain. A bilateral connectivity pattern of information flow during different exertion levels was observed by Comani *et al.* [271]. A recent study addressed the functional brain patterns and network topology during a cycling task [281]. Three graph theory measures were computed in EEG source level for six different difficulties. The local efficiency remained constant in both the alpha and beta bands, indicating that fatigue did not alter the segregation of the brain network. The alpha global efficiency is significantly changed between pre- and post-cycling due to the great requirement for alertness. However, the density of the network is decreased in the beta band during the high endurance stage, demonstrating the influence of the decision-making process.

F. CONNECTIVITY STUDIES OF PERCEPTION
The study of perception requires comparisons between several cognitive functions (e.g., attention, consciousness, and memory) and the duration of the task. One study reported significant changes in the theta band phase-synchronized coupling in the fronto-parietal area during a target recognition task [262]. Furthermore, low modularity, high clustering, and strong interactions among node hubs are evident during the cognitive processing of targets. The time spent on a task directly affects the emotions, mood, arousal state, and cognitive load of participants [282]. Ghaderi *et al.* [143] studied nonlinear differences in the brain during a time-perception task. Two groups of participants—those that overestimated the time and those that underestimated the time—exhibited significant differences in the beta CC. Furthermore, a higher perception of task effort revealed strong beta coherence coupling in the prefrontal-motor area [271]. The global efficiency, transitivity, and degree in the overestimation group were lower than those in the underestimation group.

VI. LIMITATIONS AND FUTURE DIRECTIONS
The results of the present study reveal the growing interest in the investigation of brain connectivity with respect to the execution of specific tasks. The presented review also demonstrates that the use of graph theory metrics with EEG data yields reliable and feasible results; however, many challenges must be overcome for further progress. The application of graph theory metrics in neuroergonomics will help scientists to study connectivity patterns during everyday activities, and may provide more rich information regarding brain activity in comparison with single-channel features in everyday settings [253]. Therefore, future work should focus on the use of graph analysis measurements for different real-world applications. The studies discussed in the current review lack designs with ecological validity. The studies on fatigue and

workload tasks were conducted in well-controlled simulated environments (i.e., driving and piloting). Motion tasks were limited to finger movements such as tapping, and exertion tasks were limited to cycling activity [250]. The study of perception has been limited to the classical oddball experiment [262]. Regularly performed tasks in everyday settings such as handling, lifting, gripping, grasping, pulling, pushing, assembling, sorting, manual inspection, and lower limb movements have not been well quantified using graph theory metrics. Therefore, new exploratory studies are required to address real-world applications.

The superior temporal resolution of EEG helps to capture the rapid and dynamic changes in brain activity. Few studies have considered the flow direction of neural information. These studies have used the Granger causality, DTF, PDC, and generalized PDC to quantify the strength of the interaction and causality between two signals. These methods predict the future of signal X from the past of signal Y and vice versa. The frequency-domain method is more commonly recommended for EEG due to its ability to extract neural changes at different frequency bands [44].

Methodological choices through EEG recording, pre-processing, and analysis significantly impact the functional connectivity estimations and network topology. These include the choice of reference, the presence of artifacts, the confounding effect of volume conduction in EEG (in signal space), and the inverse problem (in source space). Hence, future research should explore the effects of different types of references on the connectivity measurements, as discussed in [118], [283]. To mitigate the volume conduction effect, less sensitive connectivity estimators to volume should be used [72], [76], [163]. Other works offer additional suggestions for reducing the effect of volume conduction, such as using spatial filters (Laplacian montage), applying current source density through the Surface Laplacian, and implementing the source space method [53], [65], [284]. Despite the application of source space methods, there is no unique method to solve the inverse problem without assumptions and limitations. Additionally, the source space method is difficult to implement, and the effect of volume conduction can never be completely abolished [165]. Overall, "*none of the proposed methods have been shown to completely overcome the limitations of the volume conduction or the field spread problems,*" as mentioned by Hassan and Wendling [53].

Several studies have focused on analyzing the static functional connectivity of EEG data. The human brain is a complex system with dynamic behavior over time. An extension, known as the dynamic brain network, has been applied to track the spatiotemporal dynamics of functional brain networks. It is based on the use of the EEG source connectivity combined with a sliding window approach [285]. Changes to reconfigurations of connectivity patterns over time have been observed in task-based [286] and even in resting state [287] studies. There is a continuous reorganization of the human brain network in response to internal and external stimuli. Novel insight into the neural mechanism has been provided

in emotional-based studies [288] and mental imagery [289]; therefore, there is potential for considering the dynamic analysis of functional brain networks in future studies.

An emerging method for the estimation and classification of the dynamic functional brain states is to apply clustering-based analysis, especially the k-means [290] from the windowed covariance matrices. Allen *et al.* [291] proposed a data-driven method to assess the dynamic functional connectivity patterns of the whole brain based on spatial independent component analysis, sliding time window correlation and k-means clustering of windowed correlation matrices. The results improved the understanding of neural shifts occurring during mental work. Other studies have applied k-means clustering to identify the functional connectivity patterns that reoccur over time and across subjects [292]–[294]. However, the method requires the setting of initial values and the number of states to achieve a good performance [295].

Many attempts have been made to minimize muscular and ocular artifacts in EEG data [296]–[299]. None of the developed methods guarantee artifact-free data. It is unknown to what extent the reduction of artifacts could influence the connectivity measurements. Filtering is used to avoid antialiasing and to eliminate the effect of direct current. However, careful selection of filtering is crucial since filtering affects the phase and amplitude of EEG signals; thus, a zero-phase filter is highly recommended.

Functional connectivity patterns and graph theory have proven to be powerful tools for the characterization of brain signals. However, the ability to use these measurements as an input parameter for developing predictive models, adaptive systems, or monitoring systems has been poorly addressed [130], [255], [300]. One of the most challenging goals in the field of neuroergonomics has been to develop smart systems that can accurately monitor and detect an operator's mental state and the intention of movements at work [129], which addresses RQ6. Another challenge in implementing graph theory is the attraction model of small-worldness, which has been used to characterize fatigue [170], [204], [210] and motion [263], [274]. As the primary features, a high CC and short PL provide a more integrated and less segregated network organization; however, the methods used to evaluate this model have some constraints that should be considered in the future [301].

Brain connectivity studies require high dimensionality statistical analysis methods that consider the multivariate connectivity edges to obtain accurate estimates of model parameters. A challenging area of research is the application of advanced statistical models in tasked-based EEG functional brain networks [43].

Another limitation is the difficulty of drawing specific conclusions, especially when using different factors, as discrepancies could stem from: (a) differences in estimations of functional connectivity [115], [132], [278]; (b) differences in threshold values [257], [265], [277], [302]; (c) differences in recording reference locations [70], [163], [283], [303]; (d) the

number of existing edges [44]; (e) sample size bias [65]; (f) factors related to participant demographics, such as gender and age [304], [305] or educational level [265], [303]; (g) the brain states of the subjects, such as healthy or pathological [8]; or (h) the inclusion of trained or untrained participants [13], [160].

Further research is needed to avoid the arbitrary selection of the threshold value in a binary network to minimize bias. Recently, the application of the minimum spanning tree results has minimized the bias observed from thresholding [206]. The chance of having a network with a high false-negative value and threshold bias motivated researchers to propose novel computational methods [110], while others implemented a weighted network since it is more informative [44]. In that case, care must be taken because variation in weight affects the network topology [107]. The unweighted network still dominates the literature since it simplifies the complexity of brain signals by eliminating the weakest connections [275]. Although several thresholding approaches have been proposed, there is no reliable method that efficiently filters brain information [113].

There exists some controversy regarding the adequate number of electrodes and the effect of the electrode number on connectivity patterns [165]. A considerable number of studies have used large numbers of electrodes [275]. Finally, the CC and PL have proven to be crucial metrics for defining functional integration and functional segregation. More attention is needed in regard to other network metrics, such as the maximum eigenvalue [208] and motifs [259].

Nodes and edges are the basic elements for the construction of a network, and their selections significantly affect the network property estimations [306]. Complex networks composed of a large number of nodes and edges require advanced methods to decompose the graph into a nested hierarchy of increasingly cohesive subgraphs [307]. Those include k-core [308], k-truss [307], and k-core-truss [309]. Furthermore, complex structures of the brain network have complex interactions between nodes and a large number of edges. Therefore advanced methods have been developed to determine the hierarchal network structures, including the Kernighan-Lin Algorithm, Spectral Bisection Method, Divisive Algorithms, Agglomerative Algorithm, and CN Agglomerative Algorithm [310].

There is a significant gap in studies on the functional brain network in females. A considerable number of experiments were conducted in males only or in both males and females. Studies have demonstrated that there are significant differences between males and females; therefore, functional brain network studies focused solely on female participants are required to address these differences. Wang *et al.* [304] suggested dividing participants uniformly according to age or gender for a more accurate observation. Moreover, the number of participants in future studies should be larger in order to achieve a higher degree of generalization.

VII. CONCLUSION

This systematic literature review highlights an increasing trend in studies on functional brain connectivity networks using task-evoked EEG data. Graph theory metrics have emerged as valuable and reliable indicators for the characterization of functional interactions based on the global integration and local segregation of information processing. We demonstrate different domains in cognitive and motor functions based on an analysis of 57 articles. We also provide information regarding the distribution of selected applications, estimation techniques for functional connectivity, graph theory metrics, the number of participants, and the number of electrodes used. Furthermore, we present an overview of functional brain connectivity and the theoretical aspects of graph theory. These results provide a useful framework for the construction of an EEG functional brain network to avoid the most common pitfalls.

A larger number of reviewed studies address cognitive functions as opposed to motor processing tasks; however, studies that demonstrate the applications of brain network analyses in real-world tasks are limited and lack designs with ecological validity. Heterogeneity in experimental results, which can be attributed to a variety of factors, led to inconsistent outcomes across studies. In practice, graph theory metrics—mainly the CC and PL—are the most frequently used metrics since they reflect the functional and global integration of the brain network. Most studies on fatigue-related tasks have confirmed a reduced ability of the human brain to integrate information. Greater task difficulty results in fewer segregation processes and more integrated networks, primarily in the low-frequency bands. The presence of an economic small-world network was demonstrated for finger movement [52], the storage and retrieval of memories [233], high workload [224, 225], increased time spent on tasks [107], and tasks involving mental fatigue [153]. An assessment of bias in the reviewed articles demonstrated a high level of bias risk. Addressing random sequence generation, allocation concealment, selective data reporting, and attrition should reduce the risk of such bias in future publications. In summary, connectome analyses using graph theory metrics may pave the way for new ideas in the field of neuroergonomics and ultimately lead to safer work designs. The findings of our systematic review should be useful for understanding computational methods that can be applied to the analysis of EEG data, primarily using graph theory.

VIII. CONTRIBUTIONS

The subject literature was screened, and methodological quality was assessed independently by LI and WK. Both authors provided intellectual contributions to the development and editing of the paper.

IX. SUPPLEMENTARY MATERIAL
A. SUPPLEMENTARY MATERIAL A
Table 5 below summarizes the relevant information from the selected articles, including the node definition, edge

TABLE 5. Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

Study #	Article	Node definition	Edge definition and direction	Graph theory metrics	Number of participants	Domain	Experiment	Primary findings
1	[265]	28 EEG channels	Synchronization likelihood Indirect	CC, PL, and σ	Group 1: Males = 14 Females = 6 Group 2: Males = 15 Females = 5	Working memory	Two-back working memory tests	Less-educated individuals exhibited more organized small-world network topologies in comparison with more highly educated individuals.
2	[242]	32 EEG channels	PLV Indirect	FC	Males = 5 Females = 7	Working memory	Finger movement	Greater phase coherence of the theta band was evident in the frontal and posterior parietal regions.
3	[147]	96 EEG channels	PDC Direct	Density, node strength, strength distribution, link reciprocity, motifs, Eglobal, and Elocal	Males = 5	Motion	Dorsal flexion	The observed increase in network edges during the movement preparation phase demonstrates the need for greater information exchange in the execution of movement tasks. Decreased accessibility and increased centrality were observed during the preparation and execution of finger movement tasks.
4	[200]	32 EEG channels	DTF Direct	FC	Males = 50	Mental fatigue	Vigilance, arithmetic tasks, and switching tasks	The FC of the alpha band in the parietal to frontal lobes was weakened, whereas the FC in the central area and middle-to-left region of the beta and alpha bands increased during mental fatigue. The middle-to-right FC of the beta bands increased after the task.
5	[263]	58 EEG channels	MI Indirect	Enodal	Males = 12	Motion	Sequential finger-tapping task	An economical small-worldness was observed in the alpha and beta bands. The Eglobal value in the alpha band did not change, whereas an increase was observed in the beta band. An increased Enodal was evident in the bilateral primary motor and left sensory areas, whereas contrasting results were found in the posterior parietal areas. The MI increased in the beta band during the task, but not in the alpha band.
6	[271]	32 EEG channels	Coherence Indirect	FC	n = 1 (gender is unknown)	Motion	Road-cycling athlete	During sustained movement, a strong FC was observed for the beta band in the frontal-motor area.
7	[251]	64 EEG channels	PLV Indirect	Elocal	Males = 1	Mental workload	Arithmetic tasks	The PLV of the alpha frequency was higher in the parieto-occipital than the prefrontal region, and the task difficulty was best reflected in the parieto-occipital functional connections.
8	[254]	256 EEG channels	PLV Indirect	Degree, number of edges, density, and betweenness	Males and females = 9	Cognitive workload	Spelling tasks	Asymmetric results from the left and right hemispheres were demonstrated by a higher density, betweenness, and node degree for the left hemisphere.
9	[56]	19 EEG channels	Synchronization	Degree, CC, and PL	Males = 12	Physical, mental, and	Walking, driving, and listening	An increase in the degree of connectivity and the CC and a decrease in the PL were observed during fatigue.

TABLE 5. *(Continued.)* Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

			likelihood Indirect			visual fatigue		
10	[253]	32 EEG channels	Magnitude square coherence Indirect	Node strength, Eglobal, Elocal, CC, PL, and σ	Males = 12 Females = 12	Working memory	Difficult calculations	During difficult mathematics, a denser alpha FC was observed in the fronto-parietal regions. The local and global alpha bands were efficient; however, the beta and gamma bands exhibited no differences in Eglobal, Elocal, or σ.
11	[203]	19 EEG channels	Horizontal visibility graph Indirect	CC and PL	Males = 12	Mental, physical, and visual fatigue	Driving, treadmill, and visual tasks	A strong FC was observed in the parietal and occipital lobes after fatigue tasks, with an increase in the CC.
12	[211]	19 EEG channels	Weighted visibility graph similarity Indirect	CC and PL	Males = 12	Mental, physical, and visual fatigue	Simulated computer driving game	An increased CC in the parietal and occipital lobes demonstrated the occurrence of fatigue.
13	[201]	64 EEG channels	PDC Directed	CC, PL, and σ	Males = 15 Females = 17	Mental fatigue	PVT	Significant increases in the weighted PL in a fatigued state and in functional connectivity in the left fronto-parietal brain region were observed.
14	[131]	64 EEG channels	PDC Direct	FC	Males = 12 Females = 14	Mental fatigue	PVT	Different patterns were observed in the right and left sensorimotor regions during a state of fatigue. The middle frontal gyrus and several motor areas were crucial for sustained attention.
15	[262]	128 EEG channels	PLV Indirect	CC, PL, modularity, and network hubs	Males = 10 Females = 8	Perception	Visual discrimination	A strong CC, interactions between hub nodes, and low modularity were observed in cognitive networks.
16	[267]	64 EEG channels	PLV Indirect	FC	Males = 9 Females = 7	Workload	Mental arithmetic task	The PLV of the theta and alpha bands in the frontal and parieto-occipital brain reflected the cognitive load.
17	[128]	32 EEG channels	DFT Direct	Network density and node strength	Males and females = 3	Motion	Motor imagery tasks	The node strength for electrode C3 was observed to be high during right-hand movements.
18	[209]	16 EEG channels	Granger causality Direct	CC, PL, Eglobal, and percentage of unconnected nodes	Males and females = 12	Mental fatigue	Simulated driving	A reduction in the ability of the human brain to integrate information was reflected by a decrease in Eglobal.
19	[260]	32 EEG channels	PLV Indirect	Σ	Males = 8	Cognitive workload	Piloting with MATB	A small-world network topology was observed for the alpha bands during a high cognitive workload.
20	[274]	21 EEG channels	Spectral coherence Indirect	Node strength, accessibility, betweenness, and eigenvector	Males = 7 Females = 3	Motion	Arm movements	The FC was found to be strong in the motor regions but weak in other regions. Less accessibility was reported in the central and motor areas during movement.

TABLE 5. *(Continued.)* Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

21	[113]	40 EEG channels	MCC Indirect	Degree, CC, PL, Elocal, and Eglobal	Males = 9 Females = 1	Cognitive workload	Driving simulator	MCC was capable of detecting cognitive impairment. A high degree of connectivity during cognitive tasks indicated strong connections, high functional segregation, and global integration.
22	[311]	19 EEG channels	Synchronization likelihood Indirect	FC	Males = 20	Fatigue	Driving	A weak FC was observed after long driving tasks.
23	[257]	16 EEG channels	PDC Direct	Degree, Elocal, Eglobal, and degree distribution	Males = 19	Workload	Playing and resting tasks	During play, Elocal was observed to be higher for the beta bands and lower for the theta bands in comparison with those for resting tasks.
24	[132]	11 EEG channels	PLI Indirect	CC, PL, σ, Eglobal, and Elocal	Males = 8 Females = 12	Mental fatigue	Attention task	During fatigue, an increased betweenness centrality was observed in the frontal cortex. The CC and PL increased over time, indicating that the brain regions were more segregated and communicated with each other less efficiently. A reduced Eglobal and enhanced Elocal implied that brain resources may be reorganized and that the concerted activities within regions were more active, whereas interactions between regions were inhibited.
25	[275]	19 EEG channels	Spectral coherence Indirect	Node strength, accessibility, betweenness, CC, centrality, and eigenvector	Males = 7 Females = 3	Motion	Left/right arm movements	The FC increased in the motor region during arm movements, and the node accessibility decreased with increases in node centrality during arm movements.
26	[210]	64 EEG channels	PLI Indirect	CC, PL, and Eglobal	Males = 18	Mental fatigue	Driving simulation	An increased CC and decreased PL were observed with mental fatigue.
27	[300]	16 EEG channels	PLV Indirect	CC, PL, Eglobal, and Elocal	Males and females = 10	Mental fatigue	Driving	The PLV was found to be able to measure changes in neuronal function.
28	[16]	64 EEG channels	Cross-coherence Indirect	Eglobal, CC, PL, Elocal, and betweenness	Males = 11 Females = 17	Working memory	N-back tasks	Memory load resulted in a higher functional integration in the theta bands and a lower functional segregation in the alpha bands. The theta PL and alpha CC were negatively correlated with reaction time, whereas the node betweenness of the theta bands was positively correlated with the reaction time.
29	[87]	64 EEG channels	Pearson correlation Indirect	FC	Males = 11 Females = 17	Mental workload	N-back and mental arithmetic	Changes related to cognitive task difficulty were found to occur in the frontal theta and beta bands based on the features obtained from the functional connectivity.
30	[208]	19 EEG channels	MI Indirect	Maximum eigenvalue and degree centrality	Males and females = 18	Mental fatigue	Mental arithmetic problems	The maximum eigenvalue increased as mental fatigue increased. The weighted degree centrality exhibited substantial changes during mental fatigue

TABLE 5. *(Continued.)* Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

31	[261]	64 EEG channels	Phase synchronization Indirect	σ	Males = 10	Mental workload	Flight simulation task with MATB	A more globally efficient but less clustered network was observed for a high-difficulty cognitive workload.
32	[259]	30 EEG channels	PDC Direct	Nodal strength and CC	Males = 10	Mental workload	Piloting with MATB	The strength changed significantly with task difficulty. A higher workload corresponded to a lower CC in the central and parietal regions.
33	[258]	64 EEG channels	PLI Indirect	Eglobal, Elocal, and Enodal	Males = 20	Mental workload	Flight simulation	The Eglobal and Elocal values for the alpha and theta bands were higher in 2D than 3D tasks. The Enodal value decreased for both the alpha and theta bands with increasing mental workload.
34	[204]	32 EEG channels	Coherence Indirect	CC and PL	Males and females = 3	Mental fatigue	Driving fatigue	A significant increase in the PL was observed for all EEG bands; however, an increase in the CC was observed only for the delta, alpha, and beta bands.
35	[278]	74 EEG channels	Spectral coherence and imaginary coherence Indirect	Weighted node degree	Males and females = 10	Motion	Motor imagery	The spectral coherence in the beta activity outperformed the imaginary coherence in the contralateral motor cortex.
36	[205]	40 EEG channels	Phase coherence Indirect	FC	Males = 12	Mental fatigue	Driving	The phase coherence for the alpha and theta bands was high after a driving task.
37	[206]	30 EEG channels	PLI Indirect	Nodes, link degree, leaf fraction, kappa, diameter, eccentricity, betweenness centrality, tree hierarchy, and degree correlation	Males = 15	Mental fatigue	Driving	The PLI was observed to be high during drowsiness. The degree of delta activity was significantly lower during alertness, whereas the delta values for betweenness centrality and kappa were higher during a state of drowsiness. The degree of theta, BC, and kappa were significantly lower during a state of alertness than during drowsiness. Moreover, the authors reported a more organized integrated network during drowsiness as compared with that during alertness for the theta frequency band.
38	[213]	64 EEG channels	Generalized PDC direct	CC, PL, and σ	Males = 40	Mental fatigue	PVT with simulation driving	A positive correlation was observed between PL and task duration, and mental fatigue increased both the CC and PL. A disruption in global integration was revealed in both fatigue tasks, whereas increased local segregation was observed only for the simulated driving task.
39	[273]	64 EEG channels	Pearson's correlation Indirect	Degree, CC, PL, betweenness centrality, and eigenvector	Males = 7 Females = 1	Motion	Motion imagery	Graph theoretical metrics were shown to be useful features for classifying different hand movement tasks, especially the local properties of the network.
40	[143]	21 EEG channels	Coherence Indirect	Degree, CC, transitivity, and Eglobal	Group 1, Case 1: Males = 11 Females = 6	Time perception	Mindfulness state task	Segregation of the beta network was found to be crucial for time perception.

TABLE 5. *(Continued.)* Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

					Group 1, Case 2: Males = 14 Females = 11 Group 2, Case 1: Males = 5 Females = 3 Group 2, Case 2: Males = 5 Females = 4			
41	[13]	62 EEG channels	DTF Direct	CC, normalized CC, normalized PL, PL, and σ	Males = 18	Workload	Piloting task (MATB)	During training, Eglobal initially decreased and subsequently increased, whereas Elocal and small-worldness exhibited opposite patterns. The centrality of nodes changed in the frontal and temporal regions.
42	[268]	60 EEG channels	PDC Direct	Degree, Eglobal, Elocal, and σ	Males = 6 Females = 11	Working memory	Sternberg item recognition	A small-world topology was evident in storage and retrieval.
43	[276]	64 EEG channels	Lagged coherence Indirect	CC, PL, and σ	Males and females = 10	Motion	Reaching and grasping movements	Movement was found to reduce the FC. The weighted PL decreased during left-hand movements.
44	[127]	64 EEG channels	PDC Direct	Betweenness, PL, CC, and σ	Males = 12 Females = 14	Mental fatigue	PVT	During mental fatigue, the PL increased and σ decreased, whereas the nodal betweenness decreased in the left-frontal and middle-central areas and increased in the right-parietal areas. A prolonged time spent on the task reduced the local level of interconnectivity.
45	[212]	14 EEG channels	Synchronization likelihood Indirect	Degree, CC, and Eglobal	Males = 10 Females = 2	Mental fatigue	Driving	A lack of awareness due to mental fatigue was demonstrated by an increase in the CC and network Eglobal in a sub-band (36–44 Hz).
46	[170]	14 EEG channels	Pearson correlation Indirect	CC and Eglobal	Males = 8 Females = 2	Mental fatigue	Driving fatigue	A dense FC was observed during fatigue, with an increase in the CC and PL as the driving time increased. The degree of FC gradually increased with time.
47	[304]	32 EEG channels	Phase synchronization Indirect	PL, CC, and degree centrality	Adults: Males and females = 5 Children: Males = 4 Females = 6	Physical fatigue	Repetitive forearm task	Different movement-related EEG potentials were observed in children and adults during physical fatigue.
48	[130]	14 EEG channels	PLI Indirect	CC and PL	Males = 14	Mental fatigue	Real driving	CC and PL were reduced during fatigue, and a weak FC was observed in the frontal-to-parietal alpha and beta bands during drowsiness.
49	[202]	62 EEG channels	Pearson correlation Indirect	Degree centrality, CC, and PL	Males = 12 Females = 4	Mental fatigue	Driving task	As the degree of fatigue increased, the FC and CC increased, whereas the PL decreased for the delta band.

TABLE 5. *(Continued.)* Characteristic path length (PL), clustering coefficient (CC), directed transfer function (DTF), electroencephalogram (EEG), global efficiency (Eglobal), local efficiency (Elocal), nodal efficiency (Enodal), functional connectivity (FC), multi-attribute task battery (MATB), minimum connected component (MCC), mutual information (MI), not mentioned in the selected article (NM), partial directed coherence (PDC), phase lag index (PLI), phase locking value (PLV), psychomotor vigilance task (PVT), region of interest (ROI), small-worldness (σ).

50	[14]	19 EEG channels	Coherence Indirect	CC, PL, transitivity, Eglobal, degree centrality, and modularity	Males and females = 12	Mental workload	Mathematical task	During problem-solving, the beta band exhibited strong connectivity with high degrees of transitivity, clustering, and modularity. The alpha band exhibited a disrupted FC with a reduction in segregation. The theta band exhibited unaltered brain network function.
51	[256]	64 EEG channels	PLV Indirect	CC, PL, Eglobal, and Elocal	Males = 33	Mental workload	Flight simulation	Increased alpha and beta bands were observed with increasing workload. The Eglobal beta pattern was evidently a unique trend.
52	[169]	9 EEG channels	MI Indirect	σ, CC, and PL	Males = 20	Mental fatigue	Arithmetic task	Mental fatigue was reflected by a strong coupling connection and a reduction in the small-world network.
53	[277]	17 ROIs	PLV Indirect	Hubs	Males = 4 Females = 8	Motion	Visuomotor	An FC pattern with hubs demonstrated the most central brain regions in a visuomotor task.
54	[250]	32 EEG channels	Partial correlation Indirect	CC	Males = 8 Females = 5	Perceived physical and mental exertion	Cycling and working memory	The partial correlation of theta bands increased in the frontal region during working memory. Initially, the theta CC increased during both tasks and subsequently decreased significantly when the task became more difficult.
55	[129]	64 EEG channels	NM	Nodal strength and CC	Males and females = 20	Mental workload	Working memory test battery	The nodal strength was higher when the workload difficulty was increased. Contrasting results were found for the CC.
56	[252]	64 EEG channels	wPLI Indirect	FC	Males and females = 15	Physical workload	Seated and walking	A strong FC was observed in all brain regions for the theta band during walking.
57	[255]	32 EEG channels	PLI Indirect	Degree centrality, modularity, CC, PL, Eglobal, and σ	Males and females = 5	Mental workload	Security inspection monitoring	During high-workload tasks, the average degree centrality between nodes was high, whereas for a low workload, the connectivity was weak. When the experts could not detect whether the blocked item was dangerous, the characteristic shortest path was the costliest. When there was no block but danger or when there was a block but no danger, the CC and degree of modularity increased. The highest Eglobal and small-worldness values were observed in cases of danger with no block. Thus, the highest coherence occurred for the target stimulus without any block.

definition, graph theory metrics, number of participants plus gender, domain, experiment, and primary findings.

REFERENCES

[1] B. Pakkenberg, "Aging and the human neocortex," *Exp. Gerontol.*, vol. 38, nos. 1–2, pp. 95–99, Jan. 2003.

[2] S. Herculano-Houzel, "The human brain in numbers: A linearly scaled-up primate brain," *Frontiers Human Neurosci.*, vol. 3, pp. 1–11, Nov. 2009.

[3] F. V. Farahani, W. Karwowski, and N. R. Lighthall, "Application of graph theory for identifying connectivity patterns in human brain networks: A systematic review," *Frontiers Neurosci.*, vol. 13, pp. 1–27, Jun. 2019.

[4] E. Bullmore and O. Sporns, "Complex brain networks: Graph theoretical analysis of structural and functional systems," *Nat. Rev. Neurosci.*, vol. 10, no. 3, p. 186, 2009.

[5] M. Rubinov and O. Sporns, "Complex network measures of brain connectivity: Uses and interpretations," *NeuroImage*, vol. 52, no. 3, pp. 1059–1069, Sep. 2010.

[6] O. Sporns, "Contributions and challenges for network models in cognitive neuroscience," *Nature Neurosci.*, vol. 17, no. 5, pp. 652–660, May 2014.

[7] O. Sporns, "The human connectome: A complex network," *Ann. New York Acad. Sci.*, vol. 1224, no. 1, pp. 109–125, Apr. 2011.

[8] C. J. Stam, "Modern network science of neurological disorders," *Nature Rev. Neurosci.*, vol. 15, no. 10, pp. 683–695, Oct. 2014.

[9] F. Vecchio, F. Miraglia, and P. M. Rossini, "Connectome: Graph theory application in functional brain network architecture," *Clin. Neurophysiol. Pract.*, vol. 2, pp. 206–213, 2017.

[10] D. S. Bassett and E. T. Bullmore, "Human brain networks in health and disease," *Current Opinion Neurol.*, vol. 22, no. 4, pp. 340–347, Aug. 2009.

[11] E. J. Pegg, J. R. Taylor, S. S. Keller, and R. Mohanraj, "Epilepsy & Behavior Interictal structural and functional connectivity in idiopathic generalized epilepsy: A systematic review of graph theoretical studies," *Epilepsy Behav.*, vol. 106, 2020, Art. no. 107013.

[12] L. Rutter, S. R. Nadar, T. Holroyd, F. W. Carver, J. Apud, D. R. Weinberger, and R. Coppola, "Graph theoretical analysis of resting magnetoencephalographic functional connectivity networks," *Frontiers Comput. Neurosci.*, vol. 7, pp. 1–21, Jun. 2013.

[13] F. Taya, Y. Sun, F. Babiloni, N. V. Thakor, and A. Bezerianos, "Topological changes in the brain network induced by the training on a piloting task: An EEG-based functional connectome approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 2, pp. 263–271, Feb. 2018.

[14] A. H. Ghaderi, M. A. Nazari, and A. H. Darooneh, "Functional brain segregation changes during demanding mathematical task," *Int. J. Neurosci.*, vol. 129, no. 9, pp. 904–915, Sep. 2019.

[15] T. P. K. Breckel, C. M. Thiel, E. T. Bullmore, A. Zalesky, A. X. Patel, and C. Giessing, "Long-term effects of attentional performance on functional brain network topology," *PLoS ONE*, vol. 8, no. 9, pp. 1–14, 2013.

[16] Z. Dai, J. de Souza, J. Lim, P. M. Ho, Y. Chen, J. Li, N. Thakor, A. Bezerianos, and Y. Sun, "EEG cortical connectivity analysis of working memory reveals topological reorganization in theta and alpha bands," *Frontiers Human Neurosci.*, vol. 11, pp. 1–13, May 2017.

[17] R. Diestel, *Graph Theory*, vol. 173. Springer, 1997.

[18] L. Euler, "Solutio problematis ad geometriam situs pertinentis," *Coment. Acad. Sci. Petropolitanae*, vol. 8, no. 1741, pp. 128–140, 1741.

[19] D. Watts and S. Strogatz, "Collective dynamics of 'small-world' networks," *Nature*, vol. 393, pp. 440–442, Jun. 1998.

[20] A.-L. Barabasi and R. Albert, "Emergence of scaling in random networks," *Science*, vol. 286, pp. 509–513, 1999.

[21] D. Moher, A. Liberati, J. Tetzlaff, and D. G. Altman, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *Int. J. Surg.*, vol. 8, no. 5, pp. 336–341, 2010.

[22] R. Parasuraman and M. Rizzo, *Neuroergonomics The Brain at Work*. 2006.

[23] R. Parasuraman and G. F. Wilson, "Putting the brain to work: Neuroergonomics past, present, and future," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 50, no. 3, pp. 468–474, Jun. 2008.

[24] R. Parasuraman, "Neuroergonomics: Research and practice," *Theor. Issues Ergonom. Sci.*, vol. 4, nos. 1–2, pp. 5–20, Jan. 2003.

[25] M. Al-Kadi, M. Reaz, and M. Ali, "Evolution of electroencephalogram signal analysis techniques during anesthesia," *Sensors*, vol. 13, no. 5, pp. 6605–6635, May 2013.

[26] M. Cohen, *Analyzing Neural Time Series Data: Theory and Practice*. Cambridge, MA, USA: MIT Press, 2014.

[27] M. Teplan, "Fundamentals of EEG measurement," *Meas. Sci. Rev.*, vol. 2, no. 2, pp. 1–11, 2002.

[28] W. O. A. S. W. Ismail, M. Hanif, S. B. Mohamed, N. Hamzah, and Z. I. Rizman, "Human emotion detection via brain waves study by using electroencephalogram (EEG)," *Int. J. Adv. Sci., Eng. Inf. Technol.*, vol. 6, no. 6, p. 1005, Dec. 2016.

[29] J. Kumar and P. Bhuvaneswari, "Analysis of electroencephalography (EEG) signals and its categorization—A study," *Procedia Eng.*, vol. 38, pp. 2525–2536, 2012.

[30] A. Chowdhury, R. Shankaran, M. Kavakli, and M. M. Haque, "Sensor applications and physiological features in Drivers' drowsiness detection: A review," *IEEE Sensors J.*, vol. 18, no. 8, pp. 3055–3067, Apr. 2018.

[31] S. Kar, M. Bhagat, and A. Routray, "EEG signal analysis for the assessment and quantification of driver's fatigue," *Transp. Res. F, Traffic Psychol. Behav.*, vol. 13, no. 5, pp. 297–306, Sep. 2010.

[32] M. Carrieri, A. Petracca, S. Lancia, S. B. Moro, S. Brigadoi, M. Spezialetti, M. Ferrari, G. Placidi, and V. Quaresima, "Prefrontal cortex activation upon a demanding virtual hand-controlled task: A new frontier for neuroergonomics," *Frontiers Human Neurosci.*, vol. 10, pp. 1–13, Feb. 2016.

[33] S. J. Luck, *An Introduction to the Event-Related Potential Technique*. Cambridge, MA, USA: MIT Press, 2014.

[34] P. M. R. Reis, F. Hebenstreit, F. Gabsteiger, V. von Tscharner, and M. Lochmann, "Methodological aspects of EEG and body dynamics measurements during motion," *Frontiers Human Neurosci.*, vol. 8, pp. 9–27, Mar. 2014.

[35] H. Jebelli, S. Hwang, and S. Lee, "EEG signal-processing framework to obtain high-quality brain waves from an off-the-shelf wearable EEG device," *J. Comput. Civ. Eng.*, vol. 32, no. 1, pp. 1–12, 2018.

[36] N. W. Churchill, K. Madsen, and M. Mørup, "The functional segregation and integration model: Mixture model representations of consistent and variable group-level connectivity in fMRI," *Neural Comput.*, vol. 28, no. 10, pp. 2250–2290, Oct. 2016.

[37] O. Sporns, G. Tononi, and R. Kötter, "The human connectome: A structural description of the human brain," *PLoS Comput. Biol.*, vol. 1, no. 4, pp. 0245–0251, 2005.

[38] L. Lee, L. M. Harrison, and A. Mechelli, "A report of the functional connectivity workshop, dusseldorf 2002," *NeuroImage*, vol. 19, no. 2, pp. 457–465, Jun. 2003.

[39] L. Lee, L. M. Harrison, and A. Mechelli, "The functional brain connectivity workshop: Report and commentary," *Network: Comput. Neural Syst.*, vol. 14, no. 2, pp. R1–R15, Jan. 2003.

[40] N. D. Iakovidou, "Graph theory at the service of electroencephalograms," *Brain Connectivity*, vol. 7, no. 3, pp. 137–151, Apr. 2017.

[41] K. J. Friston, C. D. Frith, P. F. Liddle, and R. S. J. Frackowiak, "Functional connectivity: The principal-component analysis of large (PET) data sets," *J. Cerebral Blood Flow Metabolism*, vol. 13, no. 1, pp. 5–14, Jan. 1993.

[42] K. J. Friston, "Functional and effective connectivity in neuroimaging: A synthesis," *Hum. Brain Mapping*, vol. 2, nos. 1–2, pp. 56–78, 1994.

[43] K. J. Friston, C. D. Frith, and R. S. J. Frackowiak, "Time-dependent changes in effective connectivity measured with PET," *Human Brain Mapping*, vol. 1, no. 1, pp. 69–79, 1993.

[44] F. De Vico Fallani, J. Richiardi, M. Chavez, and S. Achard, "Graph analysis of functional brain networks: Practical issues in translational neuroscience," *Phil. Trans. Roy. Soc. B, Biol. Sci.*, vol. 369, no. 1653, Oct. 2014, Art. no. 20130521.

[45] K. Friston, "Functional and effective connectivity: A review," *Brain Connect.*, vol. 1, no. 1, pp. 13–36, 2011.

[46] D. Goldenberg and A. Galván, "The use of functional and effective connectivity techniques to understand the developing brain," *Develop. Cognit. Neurosci.*, vol. 12, pp. 155–164, Apr. 2015.

[47] K. Gramann and M. Plank, *Neuroergonomics: The Brain at Work and in Everyday Life*. Amsterdam, The Netherlands: Elsevier, 2019.

[48] G. Shou, H. Yuan, C. Li, Y. Chen, Y. Chen, and L. Ding, "Whole-brain electrophysiological functional connectivity dynamics in resting-state EEG," *J. Neural Eng.*, vol. 17, no. 2, Apr. 2020, Art. no. 026016.

[49] M. E. Raichle, "A paradigm shift in functional brain imaging," *J. Neurosci.*, vol. 29, no. 41, pp. 12729–12734, Oct. 2009.

[50] C. M. Michel and T. Koenig, "EEG microstates as a tool for studying the temporal dynamics of whole-brain neuronal networks: A review," *NeuroImage*, vol. 180, pp. 577–593, Oct. 2018.

[51] D. Van De Ville, J. Britz, and C. M. Michel, "EEG microstate sequences in healthy humans at rest reveal scale-free dynamics," *Proc. Nat. Acad. Sci. USA*, vol. 107, no. 42, pp. 18179–18184, Oct. 2010.

[52] G. C. O'Neill, P. Tewarie, D. Vidaurre, L. Liuzzi, M. W. Woolrich, and M. J. Brookes, "Dynamics of large-scale electrophysiological networks: A technical review," *NeuroImage*, vol. 180, pp. 559–576, Oct. 2018.

[53] M. Hassan and F. Wendling, "Electroencephalography source connectivity: Toward high time/space resolution brain networks," 2018, *arXiv:1801.02549*. [Online]. Available: http://arxiv.org/abs/1801.02549

[54] C. Stam, B. Jones, G. Nolte, M. Breakspear, and P. Scheltens, "Small-world networks and functional connectivity in Alzheimer's disease," *Cerebral Cortex*, vol. 17, no. 1, pp. 92–99, Feb. 2006.

[55] Y. Liu, H. Ayaz, and P. Shewokis, "Multisubject 'learning' for mental workload classification using concurrent EEG, fNIRS, and physiological measures," *Frontiers Hum. Neurosci.*, vol. 11, p. 389, Jul. 2017.

[56] S. Kar and A. Routray, "Effect of sleep deprivation on functional connectivity of EEG channels," *IEEE Trans. Syst., Man, Cybern. Syst.*, vol. 43, no. 3, pp. 666–672, May 2013.

[57] A. F. Rabbi, K. Ivanca, A. V. Putnam, A. Musa, C. B. Thaden, and R. Fazel-Rezai, "Human performance evaluation based on EEG signal analysis: A prospective review," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Sep. 2009, pp. 1879–1882.

[58] M. Rahman, W. Karwowski, M. Fafrowicz, and P. A. Hancock, "Neuroergonomics applications of electroencephalography in physical activities: A systematic review," *Frontiers Hum. Neurosci.*, vol. 13, pp. 1–21, Jun. 2019.

[59] A. Liberati, D. G. Altman, J. Tetzlaff, C. Mulrow, P. C. Gøtzsche, J. P. A. Ioannidis, M. Clarke, P. J. Devereaux, J. Kleijnen, and D. Moher, "The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration," *PLos Med.*, vol. 6, no. 7, 2009, Art. no. e1000100.

[60] D. Moher, A. Liberati, J. Tetzlaff, and D. Altman, "Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement," *PLos Med.*, vol. 6, no. 7, 2009, Art. no. 1000097.

[61] J. Higgins, "The cochrane collaboration's tool for assessing risk of bias in randomised trials," *Brit. Med. J.*, vol. 343, no. 7829, pp. 1–9, 2011.

[62] C. J. Stam, W. de Haan, A. Daffertshofer, B. F. Jones, I. Manshanden, A. M. van Cappellen van Walsum, T. Montez, J. P. A. Verbunt, J. C. de Munck, B. W. van Dijk, H. W. Berendse, and P. Scheltens, "Graph theoretical analysis of magnetoencephalographic functional connectivity in Alzheimer's disease," *Brain*, vol. 132, no. 1, pp. 213–224, Jan. 2009.

[63] A. Fingelkurts, A. Fingelkurts, and S. Kahkonen, "Functional connectivity in the brain—Is it an elusive concept?" *Neurosci. Biobehav. Rev.*, vol. 28, no. 8, pp. 827–836, 2005.

[64] K. J. Blinowska, "Methods for determination of functional connectivity in brain," in *Proc. IFMBE*, vol. 28, 2010, pp. 195–198.

[65] A. M. Bastos and J.-M. Schoffelen, "A tutorial review of functional connectivity analysis methods and their interpretational pitfalls," *Frontiers Syst. Neurosci.*, vol. 9, pp. 1–23, Jan. 2016.

[66] L. Marzetti, A. Basti, F. Chella, A. D'Andrea, J. Syrjälä, and V. Pizzella, "Brain functional connectivity through phase coupling of neuronal oscillations: A perspective from magnetoencephalography," *Frontiers Neurosci.*, vol. 13, pp. 1–21, Sep. 2019.

[67] M. J. Kaminski and K. J. Blinowska, "A new method of the description of the information flow in the brain structures," *Biol. Cybern.*, vol. 65, no. 3, pp. 203–210, Jul. 1991.

[68] M. Kami ski, M. Ding, W. A. Truccolo, and S. L. Bressler, "Evaluating causal relations in neural systems: Granger causality, directed transfer function and statistical assessment of significance," *Biol. Cybern.*, vol. 85, no. 2, pp. 145–157, Aug. 2001.

[69] C. Brunner, M. Billinger, M. Seeber, T. R. Mullen, and S. Makeig, "Volume conduction influences scalp-based connectivity estimates," *Frontiers Comput. Neurosci.*, vol. 10, pp. 1–4, Nov. 2016.

[70] P. Nunez, R. Srinivasan, A. F. Westdorp, R. S. Wijesinghe, D. M. Tucker, R. B. Silberstein, and P. J. Cadusch, "EEG coherency: I: Statistics, reference electrode, volume conduction, Laplacians, cortical imaging, and interpretation at multiple scales," *Electroencephalogr. Clin. Neurophysiol.*, vol. 103, no. 5, pp. 499–515, 1997.

[71] J.-P. Lachaux, E. Rodriguez, J. Martinerie, and F. J. Varela, "Measuring phase synchrony in brain signals," *Human Brain Mapping*, vol. 8, no. 4, pp. 194–208, 1999.

[72] M. Vinck, R. Oostenveld, M. van Wingerden, F. Battaglia, and C. M. A. Pennartz, "An improved index of phase-synchronization for electrophysiological data in the presence of volume-conduction, noise and sample-size bias," *NeuroImage*, vol. 55, no. 4, pp. 1548–1565, Apr. 2011.

[73] M. Paluš, "Detecting phase synchronization in noisy systems," *Phys. Lett. A*, vol. 235, no. 4, pp. 341–351, Nov. 1997.

[74] C. J. Stam and B. W. van Dijk, "Synchronization likelihood: An unbiased measure of generalized synchronization in multivariate data sets," *Phys. D, Nonlinear Phenomena*, vol. 163, nos. 3–4, pp. 236–251, Mar. 2002.

[75] C. Granger, "Investigating causal relations by econometric models and cross-spectral methods," *Econometrica*, vol. 37, no. 3, pp. 424–438, 1969.

[76] G. Nolte, O. Bai, L. Wheaton, Z. Mari, S. Vorbach, and M. Hallett, "Identifying true brain interaction from EEG data using the imaginary part of coherency," *Clin. Neurophysiol.*, vol. 115, no. 10, pp. 2292–2307, Oct. 2004.

[77] L. A. Baccalá and K. Sameshima, "Partial directed coherence: A new concept in neural structure determination," *Biol. Cybern.*, vol. 84, no. 6, pp. 463–474, May 2001.

[78] E. Pereda, R. Q. Quiroga, and J. Bhattacharya, "Nonlinear multivariate analysis of neurophysiological signals," *Prog. Neurobiol.*, vol. 77, nos. 1–2, pp. 1–37, Sep. 2005.

[79] M. Christodoulakis, M. Anastasiadou, S. S. Papacostas, E. S. Papathanasiou, and G. D. Mitsis, "Investigation of network brain dynamics from EEG measurements in patients with epilepsy using graph-theoretic approaches," in *Proc. IEEE 12th Int. Conf. Bioinf. Bioeng. (BIBE)*, Nov. 2012, p. 303.

[80] E. van Dellen, L. Douw, J. C. Baayen, J. J. Heimans, S. C. Ponten, W. P. Vandertop, D. N. Velis, C. J. Stam, and J. C. Reijneveld, "Long-term effects of temporal lobe epilepsy on local neural networks: A graph theoretical analysis of corticography recordings," *PLoS ONE*, vol. 4, no. 11, p. e8081, Nov. 2009.

[81] K. P. Westlake and S. S. Nagarajan, "Functional connectivity in relation to motor performance and recovery after stroke," *Frontiers Syst. Neurosci.*, vol. 5, pp. 1–12, Mar. 2011.

[82] M. E. J. Newman, "The structure and function of complex networks," *SIAM Rev.*, vol. 45, no. 2, pp. 167–256, 2003.

[83] J. Liu, M. Li, Y. Pan, W. Lan, R. Zheng, F.-X. Wu, and J. Wang, "Complex brain network analysis and its applications to brain disorders: A survey," *Complexity*, vol. 2017, pp. 1–27, Oct. 2017.

[84] H. Jasper, "The ten-twenty electrode system of the international federation," *Electroenceph. Clin. Neurophysiol*, vol. 10, pp. 371–375, 1958.

[85] G. E. Chatrian, E. Lettich, and P. L. Nelson, "Ten percent electrode system for topographic studies of spontaneous and evoked EEG activities," *Amer. J. EEG Technol.*, vol. 25, no. 2, pp. 83–92, Jun. 1985.

[86] R. Oostenveld and P. Praamstra, "The five percent electrode system for high-resolution EEG and ERP measurements," *Clin. Neurophysiol.*, vol. 112, no. 4, pp. 713–719, Apr. 2001.

[87] G. N. Dimitrakopoulos, I. Kakkos, Z. Dai, J. Lim, J. J. deSouza, A. Bezerianos, and Y. Sun, "Task-independent mental workload classification based upon common multiband EEG cortical connectivity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 11, pp. 1940–1949, Nov. 2017.

[88] A. Zalesky, A. Fornito, and E. T. Bullmore, "Network-based statistic: Identifying differences in brain networks," *NeuroImage*, vol. 53, no. 4, pp. 1197–1207, 2010.

[89] N. Tzourio-Mazoyer, B. Landeau, D. Papathanassiou, F. Crivello, O. Etard, N. Delcroix, B. Mazoyer, and M. Joliot, "Automated anatomical labeling of activations in SPM using a macroscopic anatomical parcellation of the MNI MRI single-subject brain," *NeuroImage*, vol. 15, no. 1, pp. 273–289, Jan. 2002.

[90] S. Baillet, J. C. Mosher, and R. M. Leahy, "Electromagnetic brain mapping," *IEEE Signal Process. Mag.*, vol. 18, no. 6, pp. 14–30, Nov. 2001.

[91] C. Michel, M. Murray, G. Lantz, S. Gonzalez, L. Spinelli, and R. Peralta, "EEG source imaging," *Clin. Neurophysiol.*, vol. 115, no. 10, pp. 2195–2222, 2004.

[92] R. D. Pascual-Marqui, C. M. Michel, and D. Lehmann, "Low resolution electromagnetic tomography: A new method for localizing electrical activity in the brain," *Int. J. Psychophysiol.*, vol. 18, no. 1, pp. 49–65, Oct. 1994.

[93] R. Pascual-Marqui, "Standardized low-resolution brain electromagnetic tomography (sLORETA): Technical details.," *Methods Find Exp. Clin. Pharmacol.*, vol. 24, pp. 5–12, Jan. 2002.

[94] M. S. Hämäläinen and R. J. Ilmoniemi, "Interpreting magnetic fields of the brain: Minimum norm estimates," *Med. Biol. Eng. Comput.*, vol. 32, no. 1, pp. 35–42, Jan. 1994.

[95] R. S. Desikan, F. Ségonne, B. Fischl, B. T. Quinn, B. C. Dickerson, D. Blacker, R. L. Buckner, A. M. Dale, R. P. Maguire, B. T. Hyman, M. S. Albert, and R. J. Killiany, "An automated labeling system for subdividing the human cerebral cortex on MRI scans into gyral based regions of interest," *NeuroImage*, vol. 31, no. 3, pp. 968–980, Jul. 2006.

[96] N. Bigdely-Shamlo, T. Mullen, C. Kothe, K.-M. Su, and K. A. Robbins, "The PREP pipeline: Standardized preprocessing for large-scale EEG analysis," *Frontiers Neuroinf.*, vol. 9, pp. 1–19, Jun. 2015.

[97] T. Bulea, A. Kilicarslan, R. Ozdemir, W. Paloski, and J. Contreras-Vidal, "Simultaneous scalp electroencephalography (EEG), electromyography (EMG), and whole-body segmental inertial recording for multi-modal neural decoding," *J. Vis. Exp.*, vol. 77, p. e50602, 2013.

[98] N. Sethi, P. Sethi, J. Torgovnick, and E. Arsura, "Physiological and non-physiological EEG artifacts," *Internet J. Neuromonitoring*, vol. 5, no. 2, pp. 3–5, 2006.

[99] G. Ruffini, S. Dunne, E. Farrés, J. Marco-Pallarés, C. Ray, E. Mendoza, R. Silva, and C. Grau, "A dry electrophysiology electrode using CNT arrays," *Sens. Actuators A, Phys.*, vol. 132, no. 1, pp. 34–41, Nov. 2006.

[100] I. Daly, F. Pichiorri, J. Faller, V. Kaiser, A. Kreilinger, R. Scherer, G. Müller-Putz, "What does clean EEG look like?" in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, May 2014, pp. 3963–3966.

[101] M. K. Islam, A. Rastegarnia, and Z. Yang, "Methods for artifact detection and removal from scalp EEG: A review," *Neurophysiologie Clinique/Clin. Neurophysiol.*, vol. 46, nos. 4–5, pp. 287–305, Nov. 2016.

[102] M. Kaiser, "A tutorial in connectome analysis: Topological and spatial features of brain networks," *NeuroImage*, vol. 57, no. 3, pp. 892–907, Aug. 2011.

[103] J. Toppi, F. De Vico Fallani, G. Vecchiato, A. G. Maglione, F. Cincotti, D. Mattia, S. Salinari, F. Babiloni, and L. Astolfi, "How the statistical validation of functional connectivity patterns can prevent erroneous definition of small-world properties of a brain connectivity network," *Comput. Math. Methods Med.*, vol. 2012, pp. 1–13, Aug. 2012.

[104] B. C. M. van Wijk, C. J. Stam, and A. Daffertshofer, "Comparing brain networks of different size and connectivity density using graph theory," *PLoS ONE*, vol. 5, no. 10, Oct. 2010, Art. no. e13701.

[105] D. S. Bassett, A. Meyer-lindenberg, S. Achard, T. Duke, and E. Bullmore, "Adaptive reconfiguration of fractal small-world human brain functional networks," *Proc. Nat. Acad. Sci. USA*, vol. 103, no. 51, pp. 19518–19523, 2006.

[106] S. L. Simpson, F. D. Bowman, and P. J. Laurienti, "Analyzing complex functional brain networks: Fusing statistics and network science to understand the brain," *Statist. Surv.*, vol. 7, no. 1, pp. 1–36, 2013.

[107] A. Fornito, A. Zalesky, and M. Breakspear, "Graph analysis of the human connectome: Promise, progress, and pitfalls," *NeuroImage*, vol. 80, pp. 426–444, Oct. 2013.

[108] H. C. Baggio, A. Abos, B. Segura, A. Campabadal, A. Garcia-Diaz, C. Uribe, Y. Compta, M. J. Marti, F. Valldeoriola, and C. Junque, "Statistical inference in brain graphs using threshold-free network-based statistics," *Hum. Brain Mapping*, vol. 39, no. 6, pp. 2289–2302, Jun. 2018.

[109] G. Varoquaux and R. C. Craddock, "Learning and comparing functional connectomes across subjects," *NeuroImage*, vol. 80, pp. 405–415, Oct. 2013.

[110] M. Drakesmith, K. Caeyenberghs, A. Dutt, G. Lewis, A. S. David, and D. K. Jones, "Overcoming the effects of false positives and threshold bias in graph theoretical analyses of neuroimaging data," *NeuroImage*, vol. 118, pp. 313–333, Sep. 2015.

[111] P. Tewarie, E. van Dellen, A. Hillebrand, and C. J. Stam, "The minimum spanning tree: An unbiased method for brain network analysis," *NeuroImage*, vol. 104, pp. 177–188, Jan. 2015.

[112] C. J. Stam, P. Tewarie, E. Van Dellen, E. C. W. van Straaten, A. Hillebrand, and P. Van Mieghem, "The trees and the forest: Characterization of complex brain networks with minimum spanning trees," *Int. J. Psychophysiol.*, vol. 92, no. 3, pp. 129–138, Jun. 2014.

[113] R. Vijayalakshmi, D. Nandagopal, N. Dasari, B. Cocks, N. Dahal, and M. Thilaga, "Minimum connected component—A novel approach to detection of cognitive load induced changes in functional brain networks," *Neurocomputing*, vol. 170, pp. 15–31, Dec. 2015.

[114] K. J. Blinowska, "Review of the methods of determination of directed connectivity from multichannel data," *Med. Biol. Eng. Comput.*, vol. 49, no. 5, pp. 521–529, May 2011.

[115] F. Wendling, K. Ansari-Asl, F. Bartolomei, and L. Senhadji, "From EEG signals to brain connectivity: A model-based evaluation of interdependence measures," *J. Neurosci. Methods*, vol. 183, no. 1, pp. 9–18, Sep. 2009.

[116] O. David, D. Cosmelli, and K. J. Friston, "Evaluation of different measures of functional connectivity using a neural mass model," *NeuroImage*, vol. 21, no. 2, pp. 659–673, Feb. 2004.

[117] L. S. Imperatori, M. Betta, L. Cecchetti, A. Canales-Johnson, E. Ricciardi, F. Siclari, P. Pietrini, S. Chennu, and G. Bernardi, "EEG functional connectivity metrics wPLI and wSMI account for distinct types of brain functional interactions," *Sci. Rep.*, vol. 9, no. 1, pp. 1–15, Dec. 2019.

[118] F. Chella, V. Pizzella, F. Zappasodi, and L. Marzetti, "Impact of the reference choice on scalp EEG connectivity estimation," *J. Neural Eng.*, vol. 13, no. 3, Jun. 2016, Art. no. 036016.

[119] L. Astolfi, F. Cincotti, D. Mattia, M. G. Marciani, L. A. Baccala, F. de Vico Fallani, S. Salinari, M. Ursino, M. Zavaglia, L. Ding, J. C. Edgar, G. A. Miller, B. He, and F. Babiloni, "Comparison of different cortical connectivity estimators for high-resolution EEG recordings," *Hum. Brain Mapping*, vol. 28, no. 2, pp. 143–157, 2007.

[120] M. Z. Baig and M. Kavakli, "Connectivity analysis using functional brain networks to evaluate cognitive activity during 3D modelling," *Brain Sci.*, vol. 9, no. 2, pp. 1–20, 2019.

[121] K. Ansari-Asl, L. Senhadji, J.-J. Bellanger, and F. Wendling, "Quantitative evaluation of linear and nonlinear methods characterizing interdependencies between brain signals," *Phys. Rev. E, Stat. Phys. Plasmas Fluids Relat. Interdiscip. Top.*, vol. 74, no. 3, pp. 1–16, Sep. 2006.

[122] M. Xia, J. Wang, and Y. He, "BrainNet viewer: A network visualization tool for human brain connectomics," *PLoS ONE*, vol. 8, no. 7, Jul. 2013, Art. no. e68910.

[123] T. W. Picton, S. Bentin, P. Berg, E. Donchin, S. A. Hillyard, R. Johnson, G. A. Miller, W. Ritter, D. S. Ruchkin, M. D. Rugg, and M. J. Taylor, "Guidelines for using human event-related potentials to study cognition: Recording standards and publication criteria," *Psychophysiology*, vol. 37, no. 2, pp. 127–152, Mar. 2000.

[124] S. Chen, F. D. Bowman, and Y. Xing, "Detecting and testing altered brain connectivity networks with k-partite network topology," *Comput. Statist. Data Anal.*, vol. 141, pp. 109–122, Jan. 2020.

[125] S. Chen, Y. Xing, J. Kang, P. Kochunov, and L. E. Hong, "Bayesian modeling of dependence in brain connectivity data," *Biostatistics*, vol. 21, no. 2, pp. 269–286, Sep. 2018.

[126] I. A. Higgins, S. Kundu, and Y. Guo, "Integrative Bayesian analysis of brain functional networks incorporating anatomical knowledge," *NeuroImage*, vol. 181, pp. 263–278, Nov. 2018.

[127] Y. Sun, A. Bezerianos, N. Thakor, and J. Li, "Functional brain network analysis reveals time-on-task related performance decline," in *Proc. 40th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2018, pp. 271–274.

[128] P. Ghosh, A. Mazumder, S. Bhattacharyya, D. N. Tibarewala, and M. Hayashibe, "Functional connectivity analysis of motor imagery EEG signal for brain-computer interfacing application," in *Proc. IEEE/EMBS Conf. Neural Eng. (NER)*, Apr. 2015, pp. 210–213.

[129] S. Samima and M. Sarma, "EEG-based mental workload estimation," in *Proc. 41st Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2019, pp. 5605–5608.

[130] J. Chen, H. Wang, Q. Wang, and C. Hua, "Exploring the fatigue affecting electroencephalography based functional brain networks during real driving in young males," *Neuropsychologia*, vol. 129, pp. 200–211, Jun. 2019.

[131] Y. Sun, J. Lim, J. Meng, K. Kwok, N. Thakor, and A. Bezerianos, "Discriminative analysis of brain functional connectivity patterns for mental fatigue classification," *Ann. Biomed. Eng.*, vol. 42, no. 10, pp. 2084–2094, Oct. 2014.

[132] J. Li, J. Lim, Y. Chen, K. Wong, N. Thakor, A. Bezerianos, and Y. Sun, "Mid-task break improves global integration of functional connectivity in lower alpha band," *Frontiers Human Neurosci.*, vol. 10, pp. 1–12, Jun. 2016.

[133] V. Latora and M. Marchiori, "Efficient behavior of small-world networks," *Phys. Rev. Lett.*, vol. 87, no. 19, pp. 198701-1–198701-4, Oct. 2001.

[134] S. Achard and E. Bullmore, "Efficiency and cost of economical brain functional networks," *PLoS Comput. Biol.*, vol. 3, no. 2, pp. 0174–0183, 2007.

[135] S. Boccaletti, V. Latora, Y. Moreno, M. Chavez, and D. U. Hwang, "Complex network:Structure and dynamics," *Phys. Rep.*, vol. 424, nos. 4–5, pp. 175–308, 2006.

[136] C. Stam and J. Reijneveld, "Graph theoretical analysis of complex networks in the brain," *Nonlinear Biomed. Phys.*, vol. 1, no. 1, p. 3, 2007.

[137] J. Wang, "Graph-based network analysis of resting-state functional MRI," *Frontiers Syst. Neurosci.*, vol. 4, pp. 1–14, June 2010.

[138] M. Hassan, M. Shamas, M. Khalil, W. El Falou, and F. Wendling, "EEGNET: An open source tool for analyzing and visualizing M/EEG connectome," *PLoS ONE*, vol. 10, no. 9, Sep. 2015, Art. no. e0138297.

[139] M. Shamas, F. Wendling, W. El Falou, and M. Hassan, "EEGNET: A novel tool for processing and mapping EEG functional networks," in *Proc. Int. IEEE/EMBS Conf. Neural Eng. NER*, Jul. 2015, pp. 1064–1067.

[140] J. C. Reijneveld, S. C. Ponten, H. W. Berendse, and C. J. Stam, "The application of graph theoretical analysis to complex networks in the brain," *Clin. Neurophysiol.*, vol. 118, no. 11, pp. 2317–2331, Nov. 2007.

[141] V. Latora and M. Marchiori, "Economic small-world behavior in weighted networks," *Eur. Phys. J. B, Condens. Matter Complex Syst.*, vol. 32, no. 2, pp. 249–263, Mar. 2003.

[142] P. Qi, H. Ru, L. Gao, X. Zhang, T. Zhou, Y. Tian, N. Thakor, A. Bezerianos, J. Li, and Y. Sun, "Neural mechanisms of mental fatigue revisited: New insights from the brain connectome," *Engineering*, vol. 5, no. 2, pp. 276–286, Apr. 2019.

[143] A. Ghaderi, S. Moradkhani, A. Haghighatfard, F. Akrami, Z. Khayyer, and F. Balcí, "Time estimation and beta segregation: An EEG study and graph theoretical approach," *PLoS ONE*, vol. 13, no. 4, pp. 1–16, 2018.

[144] M. D. Humphries, K. Gurney, and T. J. Prescott, "The brainstem reticular formation is a small-world, not scale-free, network," *Proc. Roy. Soc. B, Biol. Sci.*, vol. 273, no. 1585, pp. 503–511, Feb. 2006.

[145] M. D. Humphries and K. Gurney, "Network 'small-world-ness': A quantitative method for determining canonical network equivalence," *PLoS ONE*, vol. 3, no. 4, Apr. 2008, Art. no. e0002051.

[146] S. R. Januchowski-Hartley, V. M. Adams, and V. Hermoso, "The need for spatially explicit quantification of benefits in invasive-species management," *Conservation Biol.*, vol. 32, no. 2, pp. 287–293, Apr. 2018.

[147] F. De Vico Fallani, L. Astolfi, F. Cincotti, D. Mattia, A. Tocci, S. Salinari, M. G. Marciani, H. Witte, A. Colosimo, and F. Babiloni, "Brain network analysis from high-resolution EEG recordings by the application of theoretical graph indexes," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 5, pp. 442–452, Oct. 2008.

[148] M. E. J. Newman, "Assortative mixing in networks," *Phys. Rev. Lett.*, vol. 89, no. 20, pp. 1–4, Oct. 2002.

[149] C. J. Stam, "Characterization of anatomical and functional connectivity in the brain: A complex networks perspective," *Int. J. Psychophysiol.*, vol. 77, no. 3, pp. 186–194, Sep. 2010.

[150] M. E. J. Newman, "Modularity and community structure in networks," *Proc. Nat. Acad. Sci. USA*, vol. 103, no. 23, pp. 8577–8582, Jun. 2006.

[151] O. Sporns, C. J. Honey, and R. Kötter, "Identification and classification of hubs in brain networks," *PLoS ONE*, vol. 2, no. 10, p. e1049, Oct. 2007.

[152] R. GeethaRamani and K. Sivaselvi, "Human brain hubs(provincial and connector) identification using centrality measures," in *Proc. sInt. Conf. Recent Trends Inf. Technol. (ICRTIT)*, 2014, pp. 1–6.

[153] S. K. Raghavan Unnithan, B. Kannan, and M. Jathavedan, "Betweenness centrality in some classes of graphs," *Int. J. Combinatorics*, vol. 2014, no. 2, pp. 1–12, 2014.

[154] K. Batool and M. A. Niazi, "Towards a methodology for validation of centrality measures in complex networks," *PLoS ONE*, vol. 9, no. 4, Apr. 2014, Art. no. e90283.

[155] L. C. Freeman, "Centrality in social networks conceptual clarification," *Social Netw.*, vol. 1, no. 3, pp. 215–239, Jan. 1978.

[156] D. S. Bassett and E. Bullmore, "Small-world brain networks," *Neuroscientist*, vol. 12, no. 6, pp. 512–523, Dec. 2006.

[157] S. Hwang, H. Jebelli, B. Choi, M. Choi, and S. Lee, "Measuring workers' emotional state during construction tasks using wearable EEG," *J. Construct. Eng. Manage.*, vol. 144, no. 7, Jul. 2018, Art. no. 04018050.

[158] R. Cohen and S. Havlin, "Scale-free networks are ultrasmall," *Phys. Rev. Lett.*, vol. 90, no. 5, p. 4, 2003.

[159] A. D. Broido and A. Clauset, "Scale-free networks are rare," *Nature Commun.*, vol. 10, no. 1, pp. 1–10, Dec. 2019.

[160] F. Taya, Y. Sun, F. Babiloni, N. Thakor, and A. Bezerianos, "Brain enhancement through cognitive training: A new insight from brain connectome," *Frontiers Syst. Neurosci.*, vol. 9, pp. 1–19, Apr. 2015.

[161] G. Smetana, C. Umscheid, S. Chang, and D. Matchar, "Methods guide for authors of systematic reviews of medical tests: A collaboration between the agency for healthcare research and quality (AHRQ) and the journal of general internal medicine," *J. Gen. Internal Med.*, vol. 27, no. 1, pp. 1–5, 2012.

[162] L. A. Baccala, K. Sameshima, and D. Y. Takahashi, "Generalized partial directed coherence," in *Proc. 15th Int. Conf. Digit. Signal Process. (DSP)*, 2007, no. 3, pp. 163–166.

[163] M. Christodoulakis, A. Hadjipapas, E. S. Papathanasiou, M. Anastasiadou, G. D. Papacostas, and S. S. Mitsis, "On the effect of volume conduction on graph theoretic measures of brain networks in epilepsy," in *Modern Electroencephalographic Assessment Techniques*, vol. 91. New York, NY, USA: Humana Press, 2015, pp. 103–130.

[164] T. M. Lau, J. T. Gwin, K. G. McDowell, and D. P. Ferris, "Weighted phase lag index stability as an artifact resistant measure to detect cognitive EEG activity during locomotion," *J. NeuroEng. Rehabil.*, vol. 9, no. 1, p. 47, 2012.

[165] M. Hassan, O. Dufor, I. Merlet, C. Berrou, and F. Wendling, "EEG source connectivity analysis: From dense array recordings to brain networks," *PLoS ONE*, vol. 9, no. 8, Aug. 2014, Art. no. e105041.

[166] G. Lantz, R. Grave de Peralta, L. Spinelli, M. Seeck, and C. M. Michel, "Epileptic source localization with high density EEG: How many electrodes are needed?" *Clin. Neurophysiol.*, vol. 114, no. 1, pp. 63–69, Jan. 2003.

[167] J. Song, C. Davey, C. Poulsen, P. Luu, S. Turovets, E. Anderson, K. Li, and D. Tucker, "EEG source localization: Sensor density and head surface coverage," *J. Neurosci. Methods*, vol. 256, pp. 9–21, Dec. 2015.

[168] J. García-Prieto, R. Bajo, and E. Pereda, "Efficient computation of functional brain networks: Toward real-time functional connectivity," *Frontiers Neuroinf.*, vol. 11, pp. 1–18, Feb. 2017.

[169] G. Li, Y. Luo, Z. Zhang, Y. Xu, W. Jiao, Y. Jiang, S. Huang, and C. Wang, "Effects of mental fatigue on small-world brain functional network organization," *Neural Plasticity*, vol. 2019, pp. 1–10, Dec. 2019.

[170] F. Wang, X. Zhang, R. Fu, and G. Sun, "EEG characteristic analysis of coach bus drivers based on brain connectivity as revealed via a graph theoretical network," *RSC Adv.*, vol. 8, no. 52, pp. 29745–29755, 2018.

[171] M. Palaus, E. Marron, R. Viejo-Sobera, and D. Redolar-Ripoll, "Neural basis of video gaming: A systematic review," *Frontiers Hum. Neurosci.*, vol. 11, p. 248, May 2017.

[172] G. Borghini, L. Astolfi, G. Vecchiato, D. Mattia, and F. Babiloni, "Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness," *Neurosci. Biobehavioral Rev.*, vol. 44, pp. 58–75, Jul. 2014.

[173] S. Charbonnier, R. N. Roy, S. Bonnet, and A. Campagne, "EEG index for control operators' mental fatigue monitoring using interactions between brain regions," *Expert Syst. Appl.*, vol. 52, pp. 91–98, Jun. 2016.

[174] S. K. L. Lal and A. Craig, "Driver fatigue: Electroencephalography and psychological assessment," *Psychophysiology*, vol. 39, no. 3, pp. 313–321, May 2002.

[175] S. Majumder, B. Guragain, C. Wang, and N. Wilson, "On-board drowsiness detection using EEG: Current status and future prospects," in *Proc. IEEE Int. Conf. Electro Inf. Technol.*, May 2019, pp. 483–490.

[176] D. E. Callan and F. Dehais, *Neuroergonomics for Aviation*. Amsterdam, The Netherlands: Elsevier, 2019.

[177] P. Aricò, G. Borghini, I. Graziani, J.-P. Imbert, G. Granger, R. Benhacene, S. Pozzi, L. Napoletano, G. D. Flumeri, A. Colosimo, and F. Babiloni, "Air-traffic-controllers (ATCO): Neurophysiological analysis of training and workload," *Ital. J. Aerosp. Med.*, vol. 12, p. 35, Jun. 2015.

[178] F. Dehais, A. Duprès, S. Scannella, F. Lotte, and R. Raphaëlle, "Monitoring auditory attention with a 6 dry-electrode EEG system in real flight conditions," in *Proc. 2nd Int. Neuroergonom. Conf.*, 2018, pp. 6–9.

[179] F. Dehais, R. N. Roy, G. Durantin, T. Gateau, and D. Callan, "EEG-engagement index and auditory alarm misperception: An inattentional deafness study in actual flight condition," in *Proc. Int. Conf. Appl. Hum. Factors Ergonom.*, Jul. 2017, pp. 227–234.

[180] A. Murata, I. Kita, and W. Karwowski, "Assessment of driver's drowsiness based on fractal dimensional analysis of sitting and back pressure measurements," *Frontiers Psychol.*, vol. 9, p. 2362, Nov. 2018.

[181] M. A. S. Boksem, T. F. Meijman, and M. M. Lorist, "Effects of mental fatigue on attention: An ERP study," *Cogn. Brain Res.*, vol. 25, no. 1, pp. 107–116, Sep. 2005.

[182] E. Wascher, B. Rasch, J. Sänger, S. Hoffmann, D. Schneider, G. Rinkenauer, H. Heuer, and I. Gutberlet, "Frontal theta activity reflects distinct aspects of mental fatigue," *Biol. Psychol.*, vol. 96, pp. 57–65, Feb. 2014.

[183] S. Otmani, T. Pebayle, J. Roge, and A. Muzet, "Effect of driving duration and partial sleep deprivation on subsequent alertness and performance of car drivers," *Physiol. Behav.*, vol. 84, no. 5, pp. 715–724, Apr. 2005.

[184] C.-T. Lin, C.-H. Chuang, C.-S. Huang, S.-F. Tsai, S.-W. Lu, Y.-H. Chen, and L.-W. Ko, "Wireless and wearable EEG system for evaluating driver vigilance," *IEEE Trans. Biomed. Circuits Syst.*, vol. 8, no. 2, pp. 165–176, Apr. 2014.

[185] F. Gharagozlou, G. N. Saraji, A. Mazloumi, A. Nahvi, A. M. Nasrabadi, A. R. Foroushani, A. A. Kheradmand, M. Ashouri, and M. Samavati, "Detecting driver mental fatigue based on EEG alpha power changes during simulated driving," *Iran. J. Public Health*, vol. 44, no. 12, pp. 1693–1700, Dec. 2015.

[186] M. A. Schier, "Changes in EEG alpha power during simulated driving: A demonstration," *Int. J. Psychophysiology*, vol. 37, no. 2, pp. 155–162, Aug. 2000.

[187] L. Trejo, R. Kochavi, K. Kubitz, L. Montgomery, R. Rosipal, and B. Matthews, "EEG-based Estimation of Cognitive Fatigue," in *Proc. Int. Conf. Found. Augmented Cognition*, 2005, pp. 201–211.

[188] M. Tanaka, Y. Shigihara, A. Ishii, M. Funakura, E. Kanai, and Y. Watanabe, "Effect of mental fatigue on the central nervous system: An electroencephalography study," *Behav. Brain Funct.*, vol. 8, no. 1, pp. 8–48, 2012.

[189] C. Lafrance and M. Dumont, "Diurnal variations in the waking EEG: Comparisons with sleep latencies and subjective alertness," *J. Sleep Res.*, vol. 9, no. 3, pp. 243–248, Sep. 2000.

[190] N. R. Pal, C.-Y. Chuang, L.-W. Ko, C.-F. Chao, T.-P. Jung, S.-F. Liang, and C.-T. Lin, "EEG-based subject- and session-independent drowsiness detection: An unsupervised approach," *EURASIP J. Adv. Signal Process.*, vol. 2008, no. 1, pp. 3448–3454, Dec. 2008.

[191] S.-H. Hsu and T.-P. Jung, "Monitoring alert and drowsy states by modeling EEG source nonstationarity," *J. Neural Eng.*, vol. 14, no. 5, Oct. 2017, Art. no. 056012.

[192] C.-T. Lin, R.-C. Wu, S.-F. Liang, W.-H. Chao, Y.-J. Chen, and T.-P. Jung, "EEG-based drowsiness estimation for safety driving using independent component analysis," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 52, no. 12, pp. 2726–2738, Dec. 2005.

[193] C.-T. Lin, L.-W. Ko, I.-F. Chung, T.-Y. Huang, Y.-C. Chen, T.-P. Jung, and S.-F. Liang, "Adaptive EEG-based alertness estimation system by using ICA-based fuzzy neural networks," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 53, no. 11, pp. 2469–2476, Nov. 2006.

[194] C.-T. Lin, C.-J. Chang, B.-S. Lin, S.-H. Hung, C.-F. Chao, and I.-J. Wang, "A real-time wireless brain–computer interface system for drowsiness detection," *IEEE Trans. Biomed. Circuits Syst.*, vol. 4, no. 4, pp. 214–222, Aug. 2010.

[195] L. Trejo, K. Knuth, R. Prado, R. Rosipal, K. Kubitz, R. Kochavi, B. Matthews, and Y. Zhang, "EEG-based estimation of mental fatigue: Convergent evidence for a three-state model," in *Proc. Int. Conf. Found. Augmented Cognition*, 2007, pp. 201–211.

[196] Z. Zhang, D. Luo, Y. Rasim, Y. Li, G. Meng, J. Xu, and C. Wang, "A vehicle active safety model: Vehicle speed control based on driver vigilance detection using wearable EEG and sparse representation," *Sensors*, vol. 16, no. 2, p. 242, Feb. 2016.

[197] F.-C. Lin, L.-W. Ko, C.-H. Chuang, T.-P. Su, and C.-T. Lin, "Generalized EEG-based drowsiness prediction system by using a self-organizing neural fuzzy system," *IEEE Trans. Circuits Syst. I, Reg. Papers*, vol. 59, no. 9, pp. 2044–2055, Sep. 2012.

[198] C.-H. Chuang, Z. Cao, J.-T. King, B.-S. Wu, Y.-K. Wang, and C.-T. Lin, "Brain electrodynamic and hemodynamic signatures against fatigue during driving," *Frontiers Neurosci.*, vol. 12, pp. 1–12, Mar. 2018.

[199] C. Zhao, M. Zhao, J. Liu, and C. Zheng, "Electroencephalogram and electrocardiograph assessment of mental fatigue in a driving simulator," *Accident Anal. Prevention*, vol. 45, pp. 83–90, Mar. 2012.

[200] J.-P. Liu, C. Zhang, and C.-X. Zheng, "Estimation of the cortical functional connectivity by directed transfer function during mental fatigue," *Appl. Ergonom.*, vol. 42, no. 1, pp. 114–121, Dec. 2010.

[201] Y. Sun, J. Lim, K. Kwok, and A. Bezerianos, "Functional cortical connectivity analysis of mental fatigue unmasks hemispheric asymmetry and changes in small-world networks," *Brain Cognition*, vol. 85, pp. 220–230, Mar. 2014.

[202] C. Han, X. Sun, Y. Yang, Y. Che, and Y. Qin, "Brain complex network characteristic analysis of fatigue during simulated driving based on electroencephalogram signals," *Entropy*, vol. 21, no. 4, p. 353, Apr. 2019.

[203] A. Sengupta, S. Datta, S. Kar, and A. Routray, "EEG synchronization and brain networks: A case study in fatigue," in *Proc. Int. Conf. Med. Imag., m-Health Emerg. Commun. Syst. (MedCom)*, Nov. 2014, pp. 278–282.

[204] C. Zhao, M. Zhao, Y. Yang, J. Gao, N. Rao, and P. Lin, "The reorganization of human brain networks modulated by driving mental fatigue," *IEEE J. Biomed. Health Informat.*, vol. 21, no. 3, pp. 743–755, May 2017.

[205] J. Chen, H. Wang, and C. Hua, "Electroencephalography based fatigue detection using a novel feature fusion and extreme learning machine," *Cognit. Syst. Res.*, vol. 52, pp. 715–728, Dec. 2018.

[206] J. Chen, H. Wang, C. Hua, Q. Wang, and C. Liu, "Graph analysis of functional brain network topology using minimum spanning tree in driver drowsiness," *Cognit. Neurodynamics*, vol. 12, no. 6, pp. 569–581, Dec. 2018.

[207] J. L. Canteroa, M. Atienzaa, R. M. Salasa, and C. M. Gomez, "Alpha EEG coherence in different brain states: An electrophysiological index of the arousal level in human subjects," *Neurosci. Lett.*, vol. 271, no. 3, pp. 159–162, 1999.

[208] G. Li, B. Li, G. Wang, J. Zhang, and J. Wang, "A new method for human mental fatigue detection with several EEG channels," *J. Med. Biol. Eng.*, vol. 37, no. 2, pp. 240–247, Apr. 2017.

[209] W. Kong, W. Lin, F. Babiloni, S. Hu, and G. Borghini, "Investigating driver fatigue versus alertness using the granger causality network," *Sensors*, vol. 15, no. 8, pp. 19181–19198, Aug. 2015.

[210] B. L. Chua, Z. Dai, N. Thakor, A. Bezerianos, and Y. Sun, "Connectome pattern alterations with increment of mental fatigue in one-hour driving simulation," in *Proc. 39th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2017, pp. 4355–4358.

[211] A. Sengupta, A. Routray, and S. Kar, "Estimation of fatigue in drivers by analysis of brain networks," in *Proc. 4th Int. Conf. Emerg. Appl. Inf. Technol.*, Dec. 2014, pp. 289–293.

[212] F. Wang, H. Wang, and R. Fu, "Real-time ECG-based detection of fatigue driving using sample entropy," *Entropy*, vol. 20, no. 3, p. 196, 2018.

[213] G. N. Dimitrakopoulos, I. Kakkos, Z. Dai, H. Wang, K. Sgarbas, N. Thakor, A. Bezerianos, and Y. Sun, "Functional connectivity analysis of mental fatigue reveals different network topological alterations between driving and vigilance tasks," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 4, pp. 740–749, Apr. 2018.

[214] S. Yang, N. Ai, L. Wang, N. Yin, and G.-Z. Xu, "Research on brain functional network during mental fatigue," *Beijing Ligong Daxue Xuebao/Trans. Beijing Inst. Technol.*, vol. 37, pp. 67–71, Jun. 2017.

[215] P. Qi, L. Gao, J. Meng, N. Thakor, A. Bezerianos, and Y. Sun, "Effects of rest-break on mental fatigue recovery determined by a novel temporal brain network analysis of dynamic functional connectivity," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 1, pp. 62–71, Jan. 2020.

[216] M. S. Young, K. A. Brookhuis, C. D. Wickens, and P. A. Hancock, "State of science: Mental workload in ergonomics," *Ergonomics*, vol. 58, no. 1, pp. 1–17, Jan. 2015.

[217] R. Parasuraman and P. A. Hancock, "Adaptive control of mental workload," in *Stress, Workload and Fatigue* (Human Factors in Transportation), P. A. Hancock and P. A. Desmond, Eds. Mahwah, NJ, USA: Lawrence Erlbaum, 2001, pp. 305–320.

[218] R. Parasuraman and D. Caggiano, "Mental workload," in *Encyclopedia of the Human Brain*, vol. 3, V. S. Ramachandran, Ed. San Diego, CA, USA: Academic, 2002.

[219] P. Tsang and M. A. Vidulich, "Mental workload and situation awareness," in *Handbook of Human Factors and Ergonomics*. Hoboken, NJ, USA: Wiley, 2006.

[220] C. D. Wickens, "Multiple resources and mental workload," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 50, no. 3, pp. 449–455, Jun. 2008.

[221] A. T. Welford, "Mental work-load as a function of demand, capacity, strategy and skill," *Ergonomics*, vol. 21, no. 3, pp. 151–167, Mar. 1978.

[222] P. A. Hancock and N. Meshkati, Eds., *Human Mental Workload*. Amsterdam, The Netherlands: North Holland, 1988, pp. 139–183.

[223] S. Estes, "The workload curve: Subjective mental workload," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 57, no. 7, pp. 1174–1187, Nov. 2015.

[224] P. A. Hancock and J. K. Caird, "Experimental evaluation of a model of mental workload," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 35, no. 3, pp. 413–429, Sep. 1993.

[225] P. S. Tsang and G. Wilson, "Mental workload," in *Handbook of Human Factors and Ergonomics*, G. Salvendy, Ed., 2nd ed. New York, NY, USA: Wiley, 1997, pp. 417–449.

[226] C. D. Wickens, "Multiple resources and performance prediction," *Theor. Issues Ergonom. Sci.*, vol. 3, no. 2, pp. 159–177, Jan. 2002.

[227] P. A. Hancock and G. Matthews, "Workload and performance: Associations, insensitivities, and dissociations," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 61, no. 3, pp. 374–392, May 2019.

[228] P. A. Hancock, "A dynamic model of stress and sustained attention," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 31, no. 5, pp. 519–537, Oct. 1989.

[229] F. O. Flemisch and R. Onken, "Open a window to the cognitive work process! Pointillist analysis of man-machine interaction," *Cognition, Technol. Work*, vol. 4, no. 3, pp. 160–170, Sep. 2002.

[230] S. Loft, P. Sanderson, A. Neal, and M. Mooij, "Modeling and predicting mental workload in en route air traffic control: Critical review and broader implications," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 49, no. 3, pp. 376–399, Jun. 2007.

[231] M. S. Young and N. A. Stanton, "Mental workload," in *Handbook of Human Factors and Ergonomics Methods*, N. A. Stanton, A. Hedge, K. Brookhuis, E. Salas, and H. W. Hendrick, Eds. London, U.K.: Taylor & Francis, 2005.

[232] M. A. Just, P. A. Carpenter, and A. Miyake, "Neuroindices of cognitive workload: Neuroimaging, pupillometric and event-related potential studies of brain work," *Theor. Issues Ergonom. Sci.*, vol. 4, nos. 1–2, pp. 56–88, Jan. 2003.

[233] A. Gevins and M. E. Smith, "Neurophysiological measures of cognitive workload during human-computer interaction," *Theor. Issues Ergonom. Sci.*, vol. 4, nos. 1–2, pp. 113–131, Jan. 2003.

[234] J. Fan, J. W. Wade, A. P. Key, Z. E. Warren, and N. Sarkar, "EEG-based affect and workload recognition in a virtual driving environment for ASD intervention," *IEEE Trans. Biomed. Eng.*, vol. 65, no. 1, pp. 43–51, Jan. 2018.

[235] A. Murata, "An attempt to evaluate mental workload using wavelet transform of EEG," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 47, no. 3, pp. 498–508, Sep. 2005.

[236] M. E. Smith, A. Gevins, H. Brown, A. Karnik, and R. Du, "Monitoring task loading with multivariate EEG measures during complex forms of human-computer interaction," *Hum. Factors J. Hum. Factors Ergonom. Soc.*, vol. 43, no. 3, pp. 366–380, Sep. 2001.

[237] G. F. Wilson, "An analysis of mental workload in pilots during flight using multiple psychophysiological measures," *Int. J. Aviation Psychol.*, vol. 12, no. 1, pp. 3–18, Jan. 2002.

[238] M. Spüler, C. Walter, W. Rosenstiel, P. Gerjets, K. Moeller, and E. Klein, "EEG-based prediction of cognitive workload induced by arithmetic: A step towards online adaptation in numerical learning," *ZDM Math. Educ.*, vol. 48, no. 3, pp. 267–278, Jun. 2016.

[239] K. Moeller, G. Wood, M. Doppelmayr, and H.-C. Nuerk, "Oscillatory EEG correlates of an implicit activation of multiplication facts in the number bisection task," *Brain Res.*, vol. 1320, pp. 85–94, Mar. 2010.

[240] M. Pesonen, H. Hämäläinen, and C. M. Krause, "Brain oscillatory 4–30 Hz responses during a visual n-back memory task with varying memory load," *Brain Res.*, vol. 1138, no. 1, pp. 171–177, Mar. 2007.

[241] G. Borghini, G. Vecchiato, J. Toppi, L. Astolfi, A. Maglione, R. Isabella, C. Caltagirone, W. Kong, D. Wei, Z. Zhou, L. Polidori, S. Vitiello, and F. Babiloni, "Assessment of mental fatigue during car driving by using high resolution EEG activity and neurophysiologic indices," in *Proc. Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, vol. 70, Aug./Sep. 2012, pp. 6442–6445.

[242] P. Sauseng, J. Hoppe, W. Klimesch, C. Gerloff, and F. C. Hummel, "Dissociation of sustained attention from central executive functions: Local activity and interregional connectivity in the theta range," *Eur. J. Neurosci.*, vol. 25, no. 2, pp. 587–593, Jan. 2007.

[243] G. Borghini, P. Arico, F. Ferri, I. Graziani, S. Pozzi, L. Napoletano, J. P. Imbert, G. Granger, R. Benhacene, and F. Babiloni, "A neurophysiological training evaluation metric for air traffic management," in *Proc. 36th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc.*, Aug. 2014, pp. 3005–3008.

[244] M. Fallahi, M. Motamedzade, R. Heidarimoghadam, A. R. Soltanian, and S. Miyake, "Assessment of operators' mental workload using physiological andsubjective measures in cement, city traffic and power plant controlcenters," *Health Promotion Perspect.*, vol. 6, no. 2, pp. 96–103, Jun. 2016.

[245] S. Lei and M. Roetting, "Influence of task combination on EEG spectrum modulation for driver workload estimation," *Hum. Factors*, vol. 53, no. 2, pp. 168–179, Apr. 2011.

[246] K. Ryu and R. Myung, "Evaluation of mental workload with a combined measure based on physiological indices during a dual task of tracking and mental arithmetic," *Int. J. Ind. Ergonom.*, vol. 35, no. 11, pp. 991–1009, Nov. 2005.

[247] P. Arico, G. Borghini, G. Di Flumeri, A. Colosimo, I. Graziani, J.-P. Imbert, G. Granger, R. Benhacene, M. Terenzi, S. Pozzi, and F. Babiloni, "Reliability over time of EEG-based mental workload evaluation during air traffic management (ATM) tasks," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 7242–7245.

[248] S. Mathan, T. Feyereisen, and S. Whitlow, "WorkSense: Exploring the feasibility of human factors assessment using electrophysiological sensors," in *Proc. ICACS*, 2007.

[249] S. Puma, N. Matton, P.-V. Paubel, É. Raufaste, and R. El-Yagoubi, "Using theta and alpha band power to assess cognitive workload in multitasking environments," *Int. J. Psychophysiol.*, vol. 123, pp. 111–120, Jan. 2018.

[250] S. Porter, N. D. Silverberg, and N. Virji-Babul, "Cortical activity and network organization underlying physical and cognitive exertion in active young adult athletes: Implications for concussion," *J. Sci. Med. Sport*, vol. 22, no. 4, pp. 397–402, Apr. 2019.

[251] S. I. Dimitriadis, Y. Sun, K. Kwok, N. A. Laskaris, and A. Bezerianos, "A tensorial approach to access cognitive workload related to mental arithmetic from EEG functional connectivity estimates," in *Proc. 35th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2013, pp. 2940–2943.

[252] E. P. Shaw, J. C. Rietschel, I. M. Shuggi, Y. Xu, S. Chen, M. W. Miller, B. D. Hatfield, and R. J. Gentili, "Cerebral cortical networking for mental workload assessment under various demands during dual-task walking," *Exp. Brain Res.*, vol. 237, no. 9, pp. 2279–2295, Sep. 2019.

[253] M. A. Klados, K. Kanatsouli, I. Antoniou, F. Babiloni, V. Tsirka, P. D. Bamidis, and S. Micheloyannis, "A graph theoretical approach to study the organization of the cortical networks during different mathematical tasks," *PLoS ONE*, vol. 8, no. 8, Aug. 2013, Art. no. e71800.

[254] M. Hassan, A. Mheich, F. Wendling, O. Dufor, and C. Berrou, "Graph-based analysis of brain connectivity during spelling task," in *Proc. 2nd Int. Conf. Adv. Biomed. Eng.*, 2013, pp. 191–194.

[255] Y. Yuan, H. Wang, and P. Yuan, "Experts EEG cognitive analysis and substance classification in security inspection," *Int. J. Pattern Recognit. Artif. Intell.*, vol. 33, no. 4, pp. 1–15, 2019.

[256] I. Kakkos, G. N. Dimitrakopoulos, L. Gao, Y. Zhang, P. Qi, G. K. Matsopoulos, N. Thakor, A. Bezerianos, and Y. Sun, "Mental workload drives different reorganizations of functional cortical connectivity between 2D and 3D simulated flight experiments," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 27, no. 9, pp. 1704–1713, Sep. 2019.

[257] D. Huang, A. Ren, J. Shang, Q. Lei, Y. Zhang, Z. Yin, J. Li, K. M. von Deneen, and L. Huang, "Combining partial directed coherence and graph theory to analyse effective brain networks of different mental tasks," *Frontiers Human Neurosci.*, vol. 10, pp. 1–11, May 2016.

[258] S. Zhang, Y. Zhang, Y. Sun, N. Thakor, and A. Bezerianos, "Graph theoretical analysis of EEG functional network during multi-workload flight simulation experiment in virtual reality environment," in *Proc. 39th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Jul. 2017, pp. 3957–3960.

[259] N. Sciaraffa, G. Borghini, P. Aricò, G. Di Flumeri, A. Colosimo, A. Bezerianos, N. Thakor, and F. Babiloni, "Brain interaction during cooperation: Evaluating local properties of multiple-brain network," *Brain Sci.*, vol. 7, no. 12, p. 90, Jul. 2017.

[260] S. Ren, F. Taya, Y. Sun, J. deSouza, N. V. Thakor, and A. Bezerianos, "Assessing small-worldness of dynamic functional brain connectivity during complex tasks," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 2904–2907.

[261] S. Ren, J. Li, F. Taya, J. deSouza, N. V. Thakor, and A. Bezerianos, "Dynamic functional segregation and integration in human brain network during complex tasks," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 25, no. 6, pp. 547–556, Jun. 2017.

[262] M. Bola and B. A. Sabel, "Dynamic reorganization of brain functional networks during cognition," *NeuroImage*, vol. 114, pp. 398–413, Jul. 2015.

[263] S.-H. Jin, P. Lin, and M. Hallett, "Reorganization of brain functional small-world networks during finger movements," *Human Brain Mapping*, vol. 33, no. 4, pp. 861–872, Apr. 2012.

[264] N. Langer, C. C. von Bastian, H. Wirz, K. Oberauer, and L. Jäncke, "The effects of working memory training on functional brain network efficiency," *Cortex*, vol. 49, no. 9, pp. 2424–2438, Oct. 2013.

[265] S. Micheloyannis, E. Pachou, C. J. Stam, M. Vourkas, S. Erimaki, and V. Tsirka, "Using graph theoretical analysis of multi channel EEG to evaluate the neural efficiency hypothesis," *Neurosci. Lett.*, vol. 402, no. 3, pp. 273–277, Jul. 2006.

[266] W. Klimesch, "Memory processes, brain oscillations and EEG synchronization," *Int. J. Psychophysiol.*, vol. 24, nos. 1–2, pp. 61–100, Nov. 1996.

[267] S. I. Dimitriadis, Y. Sun, K. Kwok, N. A. Laskaris, N. Thakor, and A. Bezerianos, "Cognitive workload assessment based on the tensorial treatment of EEG estimates of cross-frequency phase interactions," *Ann. Biomed. Eng.*, vol. 43, no. 4, pp. 977–989, Apr. 2015.

[268] J. Toppi, L. Astolfi, M. Risetti, A. Anzolin, S. E. Kober, G. Wood, and D. Mattia, "Different topological properties of EEG-derived networks describe working memory phases as revealed by graph theoretical analysis," *Frontiers Human Neurosci.*, vol. 11, pp. 1–16, Jan. 2018.

[269] M. G. Kitzbichler, R. N. A. Henson, M. L. Smith, P. J. Nathan, and E. T. Bullmore, "Cognitive effort drives workspace configuration of human brain functional networks," *J. Neurosci.*, vol. 31, no. 22, pp. 8259–8270, Jun. 2011.

[270] R. Mehta, "Integrating physical and cognitive ergonomics integrating physical and cognitive ergonomics," *Trans. Occup. Ergon. Hum. Factors*, vol. 4, nos. 2–3, pp. 83–87, 2016.

[271] S. Comani, S. Di Fronso, E. Filho, A. M. Castronovo, M. Schmid, L. Bortoli, S. Conforto, C. Robazza, and M. Bertollo, "Attentional focus and functional connectivity in cycling: An EEG case study," in *Proc. 13th Medit. Conf. Med. Biol. Eng. Comput.* Cham, Switzerland: Springer, 2014, pp. 137–140.

[272] L. Cheng, H. Ayaz, J. Sun, S. Tong, and B. Onaral, "Modulation of functional connectivity and activation during preparation for hand movement," *IIE Trans. Occupational Ergonom. Hum. Factors*, vol. 4, nos. 2–3, pp. 175–187, Jul. 2016.

[273] C. Filho, R. Attux, and G. Castellano, "Can graph metrics be used for EEG-BCIs based on hand motor imagery?" *Biomed. Signal Process. Control*, vol. 40, pp. 359–365, 2018.

[274] S. F. Storti, E. Formaggio, P. Manganotti, and G. Menegaz, "Cortical network modulation during paced arm movements," in *Proc. 23rd Eur. Signal Process. Conf. (EUSIPCO)*, Aug. 2015, pp. 2596–2600.

[275] S. F. Storti, E. Formaggio, P. Manganotti, and G. Menegaz, "Brain network connectivity and topological analysis during voluntary arm movements," *Clin. EEG Neurosci.*, vol. 47, no. 4, pp. 276–290, Oct. 2016.

[276] S. Storti, I. Galazzo, P. Caliandro, C. Iacovelli, and G. Menegaz, "Connectivity modulations induced by reaching&grasping movements," in *Proc. Eur. Signal Process. Conf.*, Sep. 2018, pp. 1392–1396.

[277] T. M. P. Nguyen, X. Li, Y. Hayashi, S. Yano, and T. Kondo, "Estimation of brain dynamics under visuomotor task using functional connectivity analysis based on graph theory," in *Proc. IEEE 19th Int. Conf. Bioinf. Bioeng. (BIBE)*, Oct. 2019, pp. 577–582.

[278] T. Cattai, S. Colonnese, M. C. Corsi, D. S. Bassett, G. Scarano, and F. De Vico Fallani, "Characterization of mental states through node connectivity between brain signals," in *Proc. Eur. Signal Process. Conf.*, Sep. 2018, pp. 1377–1381.

[279] G. Borg, *Borg's Perceived Exertion and Pain Scales*. Champaign, IL, USA: Human Kinetics, 1998.

[280] J. Faulkner and R. G. Eston, "Perceived exertion research in the 21st century: Developments, reflections and questions for the future," *J. Exercise Sci. Fitness*, vol. 6, no. 1, pp. 1–14, 2008.

[281] G. Tamburro, S. di Fronso, C. Robazza, M. Bertollo, and S. Comani, "Modulation of brain functional connectivity and efficiency during an endurance cycling task: A source-level EEG and graph theory approach," *Frontiers Hum. Neurosci.*, vol. 14, pp. 1–10, Jul. 2020.

[282] S. Droit-Volet, "Time perception, emotions and mood disorders," *J. Physiol.-Paris*, vol. 107, no. 4, pp. 255–264, Sep. 2013.

[283] M. N. Anastasiadou, M. Christodoulakis, E. S. Papathanasiou, S. S. Papacostas, A. Hadjipapas, and G. D. Mitsis, "Graph theoretical characteristics of EEG-based functional brain networks in patients with epilepsy: The effect of reference choice and volume conduction," *Frontiers Neurosci.*, vol. 13, pp. 1–18, Mar. 2019.

[284] B. Burle, L. Spieser, C. Roger, L. Casini, T. Hasbroucq, and F. Vidal, "Spatial and temporal resolutions of EEG: Is it really black and white? A scalp current density view," *Int. J. Psychophysiol.*, vol. 97, no. 3, pp. 210–220, Sep. 2015.

[285] A. Kabbara, V. Paban, A. Weill, J. Modolo, and M. Hassan, "Brain network dynamics correlate with personality traits," *Brain Connect.*, vol. 10, no. 3, pp. 108–120, 2020.

[286] A. Kabbara *et al.*, "Detecting modular brain states in rest and task," *Netw. Neurosci.*, Jan. 2019, Art. no. 510727.

[287] A. Kabbara, W. E. Falou, M. Khalil, F. Wendling, and M. Hassan, "The dynamic functional core network of the human brain at rest," *Sci. Rep.*, vol. 7, no. 1, pp. 1–16, Dec. 2017.

[288] X. Liu, T. Li, C. Tang, T. Xu, P. Chen, A. Bezerianos, and H. Wang, "Emotion recognition and dynamic functional connectivity analysis based on EEG," *IEEE Access*, vol. 7, pp. 143293–143302, 2019.

[289] A. Kabbara, V. Paban, and M. Hassan, "The dynamic modular fingerprints of the human brain at rest," *BioRxiv*, 2020.

[290] A. W. Hartigan and A. John Manchek, "Algorithm AS 136: A k-means clustering algorithm," *J. Roy. Stat. Soc. C, Appl. Statist.*, vol. 28, no. 1, pp. 100–108, 1979.

[291] E. A. Allen, E. Damaraju, S. M. Plis, E. B. Erhardt, T. Eichele, and V. D. Calhoun, "Tracking whole-brain connectivity dynamics in the resting state," *Cerebral Cortex*, vol. 24, no. 3, pp. 663–676, Mar. 2014.

[292] Z. Fu, Y. Tu, X. Di, Y. Du, G. D. Pearlson, J. A. Turner, B. B. Biswal, Z. Zhang, and V. D. Calhoun, "Characterizing dynamic amplitude of low-frequency fluctuation and its relationship with dynamic functional connectivity: An application to schizophrenia," *NeuroImage*, vol. 180, pp. 619–631, Oct. 2018.

[293] S. Shakil, C.-H. Lee, and S. D. Keilholz, "Evaluation of sliding window correlation performance for characterizing dynamic functional connectivity and brain states," *NeuroImage*, vol. 133, pp. 111–128, Jun. 2016.

[294] A. S. Choe, M. B. Nebel, A. D. Barber, J. R. Cohen, Y. Xu, J. J. Pekar, B. Caffo, and M. A. Lindquist, "Comparing test-retest reliability of dynamic functional connectivity methods," *NeuroImage*, vol. 158, pp. 155–175, Sep. 2017.

[295] Q. Zhou, L. Zhang, J. Feng, and C.-Y. Z. Lo, "Tracking the main states of dynamic functional connectivity in resting state," *Frontiers Neurosci.*, vol. 13, p. 689, Jul. 2019.

[296] S. Makeig, A. J. Bell, T.-P. Jung, and T. J. Sejnowski, "Independent component analysis of electroencephalographic data," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 8, no. 3, 1996, pp. 145–151.

[297] J. A. Urigüen and B. Garcia-Zapirain, "EEG artifact removal—State-of-the-art and guidelines," *J. Neural Eng.*, vol. 12, no. 3, Jun. 2015, Art. no. 031001.

[298] S. Blum, N. S. J. Jacobsen, M. G. Bleichner, and S. Debener, "A Riemannian modification of artifact subspace reconstruction for EEG artifact handling," *Frontiers Hum. Neurosci.*, vol. 13, pp. 1–10, Apr. 2019.

[299] L. Pion-Tonachini, K. Kreutz-Delgado, and S. Makeig, "ICLabel: An automated electroencephalographic independent component classifier, dataset, and website," *NeuroImage*, vol. 198, pp. 181–197, Sep. 2019.

[300] A. Cynthia, G. Patricia, J. Nisrine, H. Mahmoud, and R. Sandy, "A new system for detecting fatigue and sleepiness using brain connectivity," in *Proc. Int. Conf. Adv. Biomed. Eng. (ICABME)*, Oct. 2017, pp. 1–4.

[301] D. Papo, M. Zanin, J. H. Martínez, and J. M. Buldú, "Beware of the small-world neuroscientist!," *Frontiers Hum. Neurosci.*, vol. 10, pp. 8–11, Mar. 2016.

[302] C. Lithari, M. A. Klados, C. Papadelis, C. Pappas, M. Albani, and P. D. Bamidis, "How does the metric choice affect brain functional connectivity networks?" *Biomed. Signal Process. Control*, vol. 7, no. 3, pp. 228–236, May 2012.

[303] S. Micheloyannis, E. Pachou, C. J. Stam, M. Breakspear, P. Bitsios, M. Vourkas, S. Erimaki, and M. Zervakis, "Small-world networks and disturbed functional connectivity in schizophrenia," *Schizophrenia Res.*, vol. 87, nos. 1–3, pp. 60–66, Oct. 2006.

[304] J. Wang, K. Yang, J. Zhang, N. Zhang, and B. Chen, "Brain function networks reveal movement-related EEG potentials associated with exercise-induced fatigue," in *Proc. ACM Int. Conf. Ser.*, vol. 1, 2018, pp. 33–40.

[305] S. Micheloyannis, M. Vourkas, V. Tsirka, E. Karakonstantaki, K. Kanatsouli, and C. J. Stam, "The influence of ageing on complex brain networks: A graph theoretical analysis," *Hum. Brain Mapping*, vol. 30, no. 1, pp. 200–208, Jan. 2009.

[306] A. Joudaki, N. Salehi, M. Jalili, and M. G. Knyazeva, "EEG-based functional brain networks: Does the network size matter?" *PLoS ONE*, vol. 7, no. 4, pp. 1–9, 2012.

[307] R. Saxena, "Capitalizing on hierarchical graph decomposition for scalable network analysis," in *Proc. CEUR Workshop*, vol. 2175, Mar. 2018, pp. 1–4.

[308] S. B. Seidman, "Network structure and minimum degree," *Social Netw.*, vol. 5, no. 3, pp. 269–287, Sep. 1983.

[309] Z. Li, Y. Lu, W.-P. Zhang, R.-H. Li, J. Guo, X. Huang, and R. Mao, "Discovering hierarchical subgraphs of K-core-truss," *Data Sci. Eng.*, vol. 3, no. 2, pp. 136–149, Jun. 2018.

[310] L. Zhang, Q. Ye, Y. Shao, C. Li, and H. Gao, "An efficient hierarchy algorithm for community detection in complex networks," *Math. Problems Eng.*, vol. 2014, pp. 1–12, Jan. 2014.

[311] H. Wang, C. Zhang, T. Shi, F. Wang, and S. Ma, "Real-time EEG-based detection of fatigue driving danger for accident prediction," *Int. J. Neural Syst.*, vol. 25, no. 2, Mar. 2015, Art. no. 1550002.

WALDEMAR KARWOWSKI (Senior Member, IEEE) received the M.S. degree in production engineering and management from the Wrocław University of Science and Technology, Poland, in 1978, the Ph.D. degree in industrial engineering from Texas Tech University in 1982, and the D.Sc. degree in management science from the Institute for Organization and Management in Industry, Poland, in 2004. He is currently a Pegasus Professor and the Chairman of the Department of Industrial Engineering and Management Systems and the Executive Director of the Institute for Advanced Systems Engineering, University of Central Florida, Orlando, USA. He has over 500 publications focused on mathematical modeling and computer simulation with applications to human systems engineering, human-centered-design, safety, neuro-fuzzy systems, nonlinear dynamics and chaos, and neuroergonomics. He is a Fellow of the Institute of Industrial Engineers (IIE), the Human Factors and Ergonomics Society (HFES), The Institute of Human Factors and Ergonomics, U.K., and the International Ergonomics Association (IEA). He is the Past President of the Human Factors and Ergonomics Society in 2007 and the International Ergonomics Association from 2000 to 2003. He has served on the Committee on Human Factors/Human Systems Integration, National Research Council, the National Academies, USA, from 2007 to 2011. He is currently the Co-Editor-in-Chief of *Theoretical Issues in Ergonomics Science* journal (Taylor & Francis, Ltd.) and the Editor-in-Chief of *Human-Intelligent Systems Integration* journal (Springer).

LINA ELSHERIF ISMAIL received the B.S. degree in industrial and management engineering from the Arab Academy for Science, Technology and Maritime Transport, Egypt, in 2012, and the M.S. degree in 2015. She is currently pursuing the Ph.D. degree with the Industrial Engineering and Management Systems Program, University of Central Florida, USA. She is currently a Teaching Assistant and a Research Assistant with the Computational Neuroergonomincs Laboratory, advised by Prof. Waldemar Karwowski. She has seven years' experience in teaching different industrial engineering undergraduate courses. Her research interests include studying the human brain signals at work and modeling the brain connectivity for providing a safe working environment.

● ● ●