International Journal of Progressive Sciences and Technologies (IJPSAT)
ISSN: 2509-0119.

Vol. 44 No. 2 May 2024, pp. 358-371

Resting-State Network Functional Connectivity Analysis: A Multimodal Imaging and Computational Modeling Approach

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Abstract—Functional connectivity is referred to as the temporal interaction between different brain regions that are spatially distant from each other. It is commonly examined during resting states by classifying resting-state functional connectivity (rs-FC) patterns and their associated synchronized activity to understand the underlying neural mechanisms that support cognitive processes. With the advancement of cutting-edge neuronal systems, multimodal imaging, and computational advances have served as promising tools for rs-FC studies. Despite having reviewed resting-state networks and their influence on a range of health anomalies in the existing literature, there nevertheless remains a lack of reviews that delve into diverse imaging modalities and computational modeling approaches for rs-FC analysis. Therefore, this systematic review aims to provide an understanding of these technologies that analyze the resting-state network functional connectivity and their correlation to cognitive functions. Through a systematic approach to analyzing studies, the most frequently employed modality was functional magnetic resonance imaging (fMRI) due to its high spatial resolution. Key findings demonstrated that higher functional connectivity levels are often linked to greater Exin ratios, which subsequently affect large-scale functional brain synchronization. Across various computational models, a non-parametric classifier has shown promise for rs-FC analysis in various contexts due to its ability to handle multiple EEG features. Moreover, the multivariate model is identified to have superior performance with a predictive area under the curve (AUC) of ~0.77. Overall, the present study underscores the vitality of using imaging and computational tools in elucidating the intricacies of rs-FC and its effects on individual cognition.

Keywords— Imaging Modalities, Simulation Models, Neural Connectivity, Baseline State, Cognitive Functions.

I. Introduction

Resting-state functional connectivity (rs-FC) is a promising component for comprehending the fundamental structure and organization of an individual brain. By examining the synchronized activity of numerous brain areas when at rest, this technique uncovers the underpinning neural networks that facilitate a wide variety of cognitive activities. Often, the connectivity may have no previously established anatomic correlation or could emanate from an indirect route via a mediating area or direct anatomic connection [1]. In recent decades, targeted functional connectivity has become the focus of many studies and a potential predictor of neurological feedback training efficacy [2]-[3]. It has been discovered that variations in functional connectivity during resting state can help distinguish individuals from a broad population [4] and have impacted how tasks are performed in several cognitive domains [5].

Techniques such as multimodal imaging and computational modeling are used in the context to understand more about the fundamental processes of human brain function and precisely how they connect to cognitive functions. Moreover, these approaches enable the functional networks involved in psychological cognition to be assessed in a more thorough and nuanced manner. The term “multimodal imaging”, also known as multiplexed imaging, is typically referring to the usage of various imaging modalities to record different facets of neural activity. Modalities including electroencephalogram (EEG), magnetoencephalography (MEG), positron emission tomography (PET), functional near-infrared spectroscopy (fNIRS), and functional magnetic resonance imaging (fMRI) are frequently employed in combination for the analysis of functional connectivity.

The integration of multiple modalities can yield a deeper understanding of the interactions between different parts of the human brain at rest, as each modality offers distinct insights into cognitive processes. For example, fNIRS is currently considered a valuable tool when used with EEG due to the absence of electro-optical interference [6]. To add on, this joint EEG-fNRIS measurement has been applied to language processing and serves as a mode of communication for individuals [7]. Nonetheless, some challenges arise when simultaneous EEG-fMRI recording is employed. This is because magnetic gradient artifacts may corrupt the inserted EEG data, and the functional images might be contaminated by artifacts derived from the electrode placement [8]. However, it is possible to analyze the fMRI data obtained during the resting state to process and generate rs-fMRI signals as depicted in Fig. 1 [9]. Undoubtedly, studies on rs-FC employing magnetic resonance imaging (MRI) have started to recognize extensive functional networks that underlie the mechanisms of cognitive and attentional regulation [10].

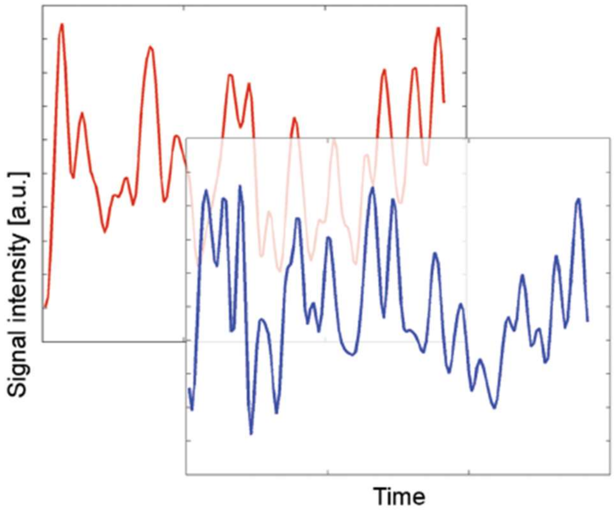

Fig. 1. The functional connectivity generated from fMRI illustrates the time course of the resting-state signals from two separate brain regions within the default mode network [9].

Meanwhile, data generated from the imaging modalities can further be analyzed using computational modeling. Technically, it leverages imaging data to create mathematical models that play vital roles in stimulating the behavior and functioning of the brain's resting-state networks. In computational modeling of resting-state networks, the use of non-parametric classifiers and semantic distance can help classify the varying states of consciousness and quantify intricate cognitive functions. Furthermore, changes in functional connectivity patterns can generally be explained by a reduction in global coupling strength in simulated whole-brain computational models [11]. To gain insight into the effect of long-term interactions across areas on the rs-FC changes, especially in clinical groups, it is crucial to estimate the model's effective connectivity (EC). The EC ideally produces the observed FCs through the optimal connection strengths among the regions within the model. Changes in rs-FC can simply be accounted for via a global shift for optimum dynamics by adjusting the model parameters in healthy intervention, as shown in Fig. 2 [12]. Overall, both multimodal imaging and computational modeling can serve as a potent way to analyze the complexities of resting-state network connectivity and its effects on psychological and cognitive behaviors.

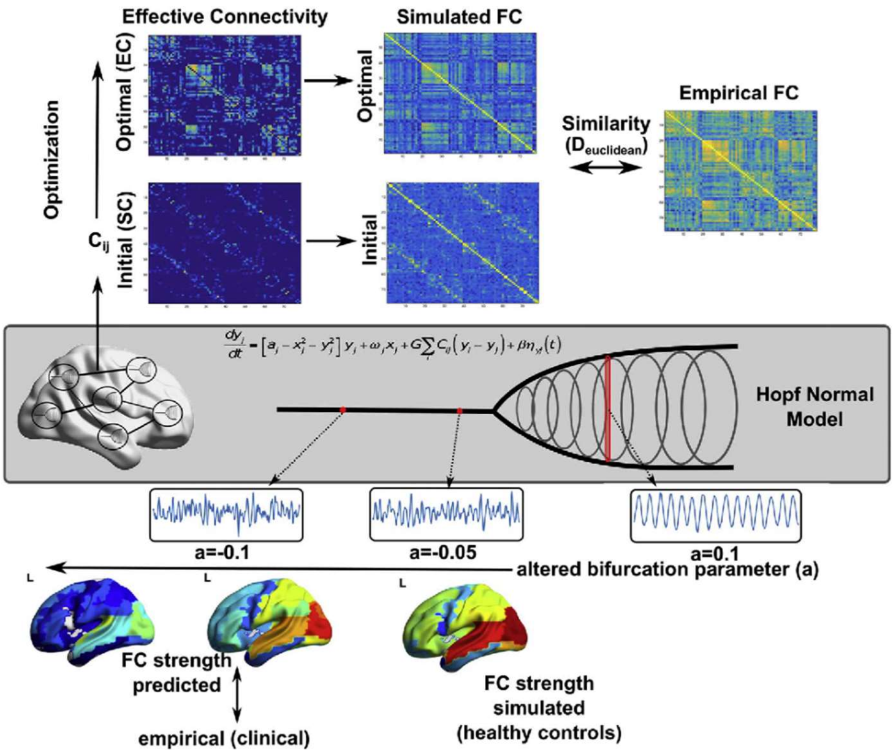

Fig. 2. Overview of the computational model used to study alterations of rs-FC that include three panels, the effective connectivity optimization, the Hopf normal model, and the overall effect of the local bifurcation parameter [12].

Several existing pieces of literature have reviewed the resting state networks [13] and their effect on various diseases and health dysfunctions [14]-[19]. This reflects a burgeoning interest in acquiring knowledge related to the intrinsic activity of the human brain and how alterations in resting-state networks could have implications. However, there is a lack of reviews regarding diverse multimodal imaging approaches and computational models for rs-FC studies. Therefore, this systematic review aims to synthesize existing studies on both multimodal imaging and computational modeling of rs-FC networks to evaluate their effectiveness and understand how these approaches can enhance the identification of psychological states and specific cognitive functions.

II. Methodology

2.1. Literature Search and Evaluation

Inclusion Criterion

Studies from relevant disciplines spanning from health science, psychology, and neuroscience to computer science and engineering that provide the required data were included. Another inclusion criterion is ensuring that the focus of the studies is on the use of multimodal imaging and computational modeling, their effects on rs-FC, and associated cognitive functions. Conversely, searched articles will be excluded if they were written in English, not within the most recent publication years, or in the form of books or conference proceedings.

2.2. Literature Identification

The literature search was facilitated by using various databases, including Google Scholar, Web of Science, Springer, and PubMed. To base the present review on the most up-to-date literature considering data retrieval and synthesis in the age of digitization, limiting the publication range date from 2014 to 2024 is crucial. By emphasizing this timeframe, it is intended to capture the latest advances in multimodal imaging and computational modeling of rs-FC. Some predefined terms and their variations correlated with resting-state, functional connectivity, multimodal imaging, and computational modeling were utilized. After conducting both a database and manual search, a total of 118 articles were identified.

2.3. Screening for Inclusion

The strategy of systematically evaluating search results to locate the studies that fit particular criteria is known as screening. To further decide the relevance of findings to this research topic, the full titles and abstracts were screened based on the predetermined inclusion criteria. As a result, 60 articles were retrieved. These studies that were deemed relevant will be subjected to another round of screening in full-text to assess their relevance in greater detail.

2.4. Eligibility Assessment

Each selected 13 full-text articles were skimmed through to assess the eligibility of the studies. Articles included for the review are those with sufficient data and fulfill all other specified criteria. This phase ensures that the studies to be included meet the requisite standards for inclusion and are pertinent to the research question. Technical reports, particularly, are not included in this review due to the lack of a peer-review process. Furthermore, articles that are not available in full-text were excluded too. Only articles with well-cited references that are of high quality were included. After meticulous review, a total of thirteen articles are selected for this systematic review. These 13 studies that met the eligibility criteria proceeded to the final analysis.

2.5. Data Extraction and Synthesis

The data to be extracted include participant characteristics, such as sample size, imaging modalities as well as computational modeling methods used, analytical approach, key results related to rs-FC, and associated cognitive-psychological attributes. Meanwhile, the synthesis concentrated on comprehending the potential of both imaging and computational models in analyzing rs-FC and the effects of rs-FC on cognitive processes and correlated psychological states. On top of that, the synthesis also highlights the knowledge gaps, explores the implications of the outcomes, and examines the trends or recurring themes across studies. The goal of data synthesis is to offer a thorough overview of the present state of study in this field, guided by the set research objectives.

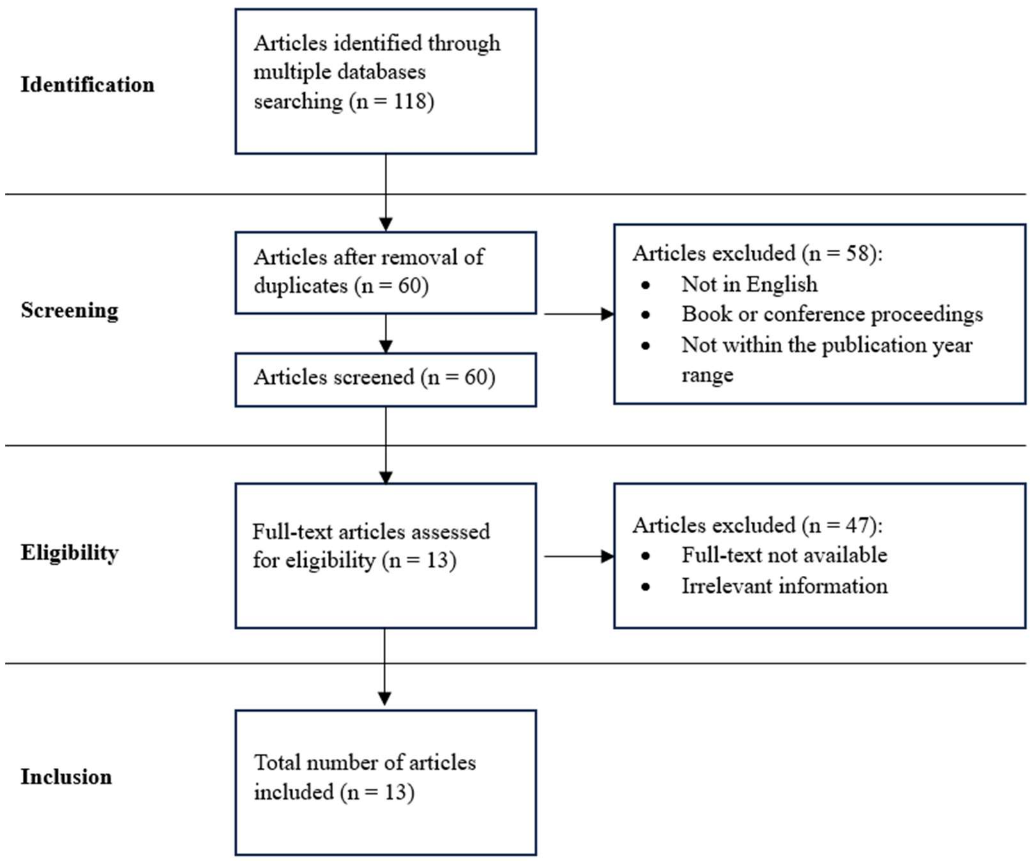

Fig. 3. Systematic review methodology.

III. RESULTS AND DISCUSSION

3.1. Multimodal Imaging

In current years, many rs-FC studies have integrated multimodal imaging modalities, particularly fMRI or rs-fMRI [20]-[27], fNIRS, and EEG [28]-[29]. However, fMRI emerges as the most widespread imaging technique because it allows for precise localization of the neural activity due to high spatial resolution. Nonetheless, fNIRS is especially beneficial in measuring hemodynamic alterations linked to brain activity since it is a non-invasive method. Generally, every modality offers distinct perspectives on brain activity and functional connectivity during resting states. A more detailed comprehension of rs-FC and its implications for psychological cognition can hence be made feasible by combining these modalities. As analyzed, most of the studies' analytical approach used is seed-based correlation [24-25, 27, 29]. This is due to its interpretability, simplicity, and sensitivity to negative and positive correlations. Although other findings may include independent component analysis (ICA) as their analytical method which can provide insightful data into brain network organization [26], seed-based correlation is still prevalent because of its capacity to target networks of interest or specific brain areas.

The study of Kocher et al., [24] determined that there was a decreased functional connectivity, particularly in the parietal and left temporal default mode network (DMN) nodes. In this context, DMN activity refers to the triggering of internal cognitive processes without external stimuli [10, 30]. As described by Andrews-Hanna et al., [31], self-generated cognition, for example, imagination and mind wandering is closely associated with DMN activation. Subsequently, the reduced connectivity has hugely impacted both language processing and verbal working memory. However, results suggested that education level could have a positive effect on DMN functional connectivity loss and related cognitive impairments. Hence, it emphasizes the significance of cognitive reserve in preserving cognitive function. Champagne et al., [25], on the other hand, discussed a comparative study between mTBI individuals and healthy controls, where greater cerebral blood flow (CBF) was observed in mTBI patients. The increased CBF may be involved in the blood oxygen level-dependent (BOLD) signal modulation, thereby compensating for impaired functional connectivity within the cortical networks. Overall, these findings indicate that changes in functional connectivity, such as DMN, can potentially be the contributing factor in cognitive deficits but can be arguably offset by cognitive reserve and compensatory mechanisms like elevated CBF.

A recent study by Premi et al., [20] focused on assessing resting-state neural activity between GRN Thr272fs mutation carriers and control groups. Due to reduced regional homogeneity (ReHo), fractional amplitude of low-frequency fluctuation (fALFF), and degree of centrality (DC) in patients, the asymptomatic GRN carrier groups exhibit altered resting-state neural activity. The outcomes imply that functional neuronal network abnormalities, despite being present in asymptomatic carriers, are a feature of GRN pathophysiology and may have on the progression of cognitive deficits in individuals. Meanwhile, the study by Ruppert et al., [26], focuses more on individuals with mild cognitive impairment (MCI) for the functional connectivity analysis. However, the results were in contrast to those of Kocher et al., [24], where increased functional connectivity was found along fronto-parietal connections. Based on these studies, it is demonstrated that rs-fMRI is an effective and sensitive imaging modality for identifying cognitive impairment in its early stages and monitoring disease progression.

The finding of Trambaiolli et al., [28] typically estimated functional connectivity with particular emphasis on fNRIS in terms of the measure of hemodynamic activity, EEG gamma, and beta bands. The predictive model revealed that there is a strong correlation between the EEG gamma-m-alpha sensorimotor cortex (CSS) and the fNIRS oxyhemoglobin variations in CSS. In general, the model has a mean absolute error of less than 20%. It suggests that hemodynamic resting-state measurements and pre-task electrophysiological data are important markers of neurofeedback performance, thereby offering an understanding of the brain mechanisms that control cognitive processes. Similarly, Sirpal et al., [29] analyze the resting-state functional connectivity using combined fNIRS and EEG. This study supported the result of Trambaiolli et al., [28], stating high-frequency EEG ranges, notably the gamma band, have been associated with fNIRS signals. This confirmed that the neural output of EEG from the human brain even at rest can be utilized to predict fNIRS signals.

In the work of Li et al., [22], selective effects were identified to occur in the functional connectivity between specific brain regions, while participants were at resting state. These changes in functional connectivity, specifically the medial prefrontal cortex and medial temporal lobe, have been discovered to be correlated with cognitive performance. Hence, it is indicated that the pattern or strength of functional connectivity between these brain regions can possibly influence an individual's level of cognitive performance or ability in older age. Conversely, van den Heuvel et al., [23] described that higher levels of intrinsic functional connectivity were determined by a greater Exin ratio. In this regard, the Exin ratio represents chemoarchitecture, which can impact functional cognitive synchronization and communication patterns. Although both the findings of Li et al., [22] and van den Heuvel et al., [23] analyzed rs-FC using fMRI, their emphasis is on different aspects. The focus of Li et al., [22] is on the role of specific networks in cognitive function, whereas van den Heuvel et al., [23] highlighted the interaction between chemical makeup and the structure of the neural networks.

Based on the study of Tewarie et al., [21], the analysis of rs-FC networks was conducted by employing coupled neural mass models, including fMRI and magnetoencephalography (MEG) data. An identifiable overlap was observed between the recordings of fMRI and MEG, in particular in the MEG alpha band. Since the MEG alpha band exhibits similar patterns to those of fMRI, they can hence offer complementary data into brain activity and functional connectivity during resting states. Moreover, the overlap strongly reflects synchronized neuronal activity within the brain regions as identified by MEG while closely aligning with regions that show synchronized blood flow fluctuations, as detected by fMRI. By connecting these brain networks, it is possible to understand their roles in different cognitive functions, such as decision-making, memory, and attention level. In contrast to Tewarie et al., [21], the recent finding of Overbeek et al., [27] studied the integration of fMRI and magnetic resonance spectroscopy (MRS) with its focus mainly on the anterior cingulate cortex (ACC). Findings revealed that the altered functional connectivity was hugely attributed to the distinguished ACC connectivity patterns. This suggests that disruptions in ACC can lead to both emotional and cognitive disturbances, affecting normal brain function. The combined approach of fMRI-MEG [21] and fMRI-MRS [27] can provide a more holistic way than merely fMRI [20, 22-23, 25] to analyze rs-FC due to precise timing information, enhanced temporal and spatial resolution, and overall increase confidence in the results.

TABLE 1. STUDIES CHARACTERISTICS AND RESULTS ON VARIOUS MULTIMODAL IMAGING.

Articles	Sample	Imaging Modalities	Analytical Approach	Key Findings	Significance
Li et al., [22]	45 older adults (26 in the intervention group and 19 in the control group)	fMRI	Comparison between the pre-and post-intervention fMRI data; assess alterations present in connectivity patterns	Selectively affecting the functional connectivity between the medial temporal lobe and medial prefrontal cortex during resting state and an individual cognitive performance	Preserve cognitive function and brain health during old age
Trambaiolli et al., [28]	31 healthy (16 women)	fNIRS and EEG	Estimate resting-state FC from each neuroimaging modality; EEG gamma and beta bands as well as fNIRS oxyhemoglobin and deoxyhemoglobin concentrations	Predictive model exhibits a relatively small average absolute error (< 20%); substantial association between fNIRS oxyhemoglobin CSS and the EEG gamma-m-alpha CSS ($r = -0.456$, $p = 0.030$)	Both pre-task electrophysiological and hemodynamic resting states play vital roles as indicators of neurofeedback performance
Kocher et al., [24]	80 patients; 80 healthy subjects	rs-fMRI, anatomical MRI, amino acid PET	Combination of ICA or seed-based correlation	Decreased functional connectivity found in both the left temporal and parietal DMN nodes may lead to deficient verbal working memory and language processing; individuals with higher education are less likely to have DMN connectivity loss and cognitive impairment	Progressive cognitive deterioration is linked to changes in the DMN
Champagne et al., [25]	23 subjects with mTBI; 27 age-matched healthy controls	rs-fMRI	Seed-based correlation	Individuals with mTBI showed substantially greater CBF0 compared to the control group	Influence of physiological modulators of BOLD signal on the FC of cortical networks
van den Heuvel et al., [23]	2 datasets; the first dataset from the human cortex and the second dataset from the macaque cortex	fMRI	Correlation coefficients between the resting-state FC values of cortical regions and Exin ration values	A higher Exin ratio demonstrated greater levels of intrinsic FC	Influence of chemoarchitecture on communication patterns and large-scale functional brain synchronization

Tewarie et al., [21]	2 datasets; 17 healthy subjects from the previous study, 68 healthy subjects with MEG data	fMRI and MEG	Coupled neural mass models	Significant overlap between MEG and fMRI recordings of resting-state FC networks, especially in the MEG alpha band	Influence of functional core network on communication amongst high-degree nodes within the structural network
Ruppert et al., [26]	2 datasets; first dataset: 16 healthy individuals, second dataset: 36 with normal cognition & 12 with MCI	FDG-PET and rsfMRI	ICA	Increased functional connectivity along fronto-parietal connections in patients MCI patients in comparison to individuals with normal cognition and control groups	Impact of hemodynamic measurements of neural network activity on cognitive symptoms
Overbeek et al., [27]	21 healthy controls; 19 individuals with first-episode psychosis	MRS, fMRI	Seed-based correlation	Distinct ACC FC between healthy controls and individuals with first-episode psychosis in some brain areas	A correlation between resting-state FC, inhibitory (GABA), and the major excitatory (glutamate)
Sirpal et al., [29]	40 epileptic individuals 27 males, 13 females	fNIRS and EEG	Seed-based correlation	The predictive fNIRS signals were higher frequency EEG ranges, in particular the gamma band	Prediction of fNIRS signals from neural data (EEG) within a resting human epileptic brain
Premi et al., [20]	38 healthy controls; 31 GRN Thr272fs mutation carriers (17 asymptomatic carriers and 14 patients)	rs-fMRI	ReHo, fALFF, DC	Altered resting-state neural activity in asymptomatic GRN carrier groups; Reduced ReHo, fALFF, and DC in patients	Characterization of GRN pathophysiology by functional neural network changes

*fMRI: functional magnetic resonance imaging, fNIRS: functional near-infrared spectroscopy, EEG: electroencephalogram, CSS: connectivity summary scores; rs-fMRI: resting-state functional MRI, PET: positron emission tomography, DMN: default-mode network, mTBI: mild traumatic brain injury, ICA: independent component analysis, CBF0: cerebral blood flow, BOLD: blood-oxygen-level-dependent, FC: functional connectivity, MEG: Magnetoencephalography, FDG-PET: [18F]-fluorodeoxyglucose positron emission tomography, MCI: mild cognitive impairment, MRS: magnetic resonance spectroscopy, ACC: anterior cingulate cortex, GABA: gamma-aminobutyric acid, ReHo: regional homogeneity, fALFF: fractional amplitude of low-frequency fluctuation, DC: degree centrality .

3.2. Computational Modeling

There are some applications of computational models that have been widely used in rs-FC analysis. This includes semantic distance measures [32], a whole-brain mean-field computational model [33], deep learning model [34] and a non-parametric classifier based on ensembles of decision trees [35]. Computational models can provide advantages in various forms, which include their role as proxies for physical connections between human brain areas at the macro and mesoscopic level [11]. Given the cutting-edge technologies, the rs-FC data can be easily analyzed to elucidate the intricate interactions that are established between various regions of the brain during rest. Valuable insights, such as neural functional architecture, individual variations in rs-FC patterns, and network dynamics can all be yielded via these models. In addition, these computational models have proven helpful in understanding the neurological underpinnings of numerous cognitive abilities [36].

A current finding by Orwig et al., [32] described the use of semantic distance measures to perform voxel-wise connectivity matrix computations. In observations, reduced connectivity in visual-temporal and parietal areas was found to be attributed to higher levels of dopamine transporter (DT), whereas greater local connectivity in the affected visual regions was highly associated with lower DT levels. This indicates that variations in rs-FC patterns might have an impact on one’s ability for creative thinking. Unlike Orwig et al., [32], the study of Hansen et al., [33] specifically delved into small non-linearities inside the human network nodes that resemble resting-state networks. This is achieved through the utilization of a whole-brain mean-field computational model, in which outcomes were compared with time-averaged functional connectivity data. The changes in the underlying neuronal processes have certainly led to a significant association discovered between resting-state neural activity and non-stationarity in functional connectivity. Underscoring the dynamic characteristics of resting-state neural networks, it is crucial to consider temporal alterations in functional connectivity when examining brain function, behavior, and cognition.

To allow for a more comprehensive analysis of EEG indicators, a non-parametric classifier was utilized, as demonstrated by Engemann et al., [35]. Through this decision trees-based approach, multiple EEG features, such as theta and alpha frequency bands can be incorporated. The resulting predictive area under the curve (AUC) of about 0.77 signifies the superior effectiveness of the multivariate computational model over univariate techniques in classifying and monitoring cognitive states. Meanwhile, the study of Fan et al., [34] employed an end-to-end deep learning model with complementary algorithms, namely a long short-term memory (LSTM) network and convolutional neural network (CNN) to analyze functional connectivity within the brain based on time-varying connectivity patterns. Despite thousands of subjects involved, the model achieved a high classification accuracy of approximately 93% which signifies the effective grouping of individuals based on functional connectivity patterns in the fMRI data. According to Pearson’s correlation coefficient results, it is interpreted that the model’s predictive power for crystallized intelligence is moderate but lower for fluid intelligence in response to rs-FC patterns. Overall, while Engemann et al., [35] focused on a single model, indicating a more traditional method, Fan et al., [34] adopted a more sophisticated approach that enabled the capturing of both temporal and spatial features present in fMRI data for a more comprehensive rs-FC analysis.

TABLE 2. STUDIES CHARACTERISTICS AND RESULTS ON VARIOUS COMPUTATIONAL MODELING.

Articles	Sample	Computational Modeling	Analytical Approach	Key Findings	Significance
Orwig et al., [32]	175 healthy adults	Semantic distance; linear regression analysis	Computed voxel-wise connectivity matrices; conduct linear regression analysis	Decreased connectivity in the parietal and visual-temporal areas due to increased DT levels; increased local connectivity inside the visual areas can lead to decreased DT levels	Differences in resting-state connectivity patterns can cause varying creative thinking ability
Hansen et al., [33]	5 healthy subjects	Whole-brain mean-field computational model	Compared the outcomes of computational models optimized with fit time-averaged FC; use simplified linear stochastic models	Observed small non-linearity within the network nodes; similar to resting state networks; broadened behavior repertoire	A significant association between non-stationarity in resting-state FC and resting-state neural activity
Engemann et al., [35]	327 samples (148 with UWS, 179 with MCS, 66 healthy controls)	Non-parametric classifier based on ensembles of decision trees	Analyzed EEG markers of consciousness; including multiple EEG features, such as alpha and theta frequency bands	The non-parametric classifier obtained a predictive AUC of ~0.77; the multivariate model has superior performance over univariate classification	Application of EEG markers of consciousness in a variety of acquisition and clinical contexts
Fan et al., [34]	1,050 individuals from Human Connectome Project	End-to-end deep learning model; CNN; LSTM network	Focused on acquisition of time-varying patterns in fMRI data	Achieved a high classification accuracy of ~93%; obtained Pearson's correlation coefficient with prediction accuracies of 0.49 and 0.31 for crystallized and fluid intelligence prediction tasks, respectively	The prediction of individualized characterization of cognition traits can be enhanced via time-varying connectivity patterns

*DT: divergent thinking, UWS: Unresponsive Wakefulness Syndrome, MCS: Minimally Conscious State, AUC: area under the curve, CNN: convolutional neural networks, LSTM: long short-term memory

3.3. Current Trends, Limitations, and Future Directions

The most recent trend of multimodal imaging is fMRI [20, 22-23, 25], particularly due to its non-invasiveness nature, overall high spatial resolution, and whole-brain coverage. However, merging various neuroimaging modalities [21, 24, 26-29] remains a common trend to obtain reliable and comprehensive data on brain activity for the analysis of rs-FC. The vitality of combining different multimodal methods, such as fMRI, fNIRS, EEG, MEG, and PET is to overcome the limits of certain modalities and examine neural processes from a wider perspective because comprehending the brain is a highly complex process. Moreover, no single imaging technique can adequately capture its structure and function. For example, while fMRI offers remarkable spatial resolution, it may have limitations in temporal resolution and addressing fine-scale neural activity [37]. The same applies to MEG and EEG, as they have great temporal resolution but limited spatial resolution [38]. Additionally, the sensitivity of MEG to magnetic interference or tangentially oriented currents that are in proximity to sensors, such as in the cortex [39] and the susceptibility of EEG to undesired noise [40] could further contribute to limitations. Hence, integrating these imaging modalities can significantly aid in studying brain function and analyzing rs-FC at multiple levels, be it at the microscopic scale of distinct neurons or the macroscopic scale of an individual's different brain regions. As an illustration, fMRI can detect the spatial localization of neural activity, while complementary modalities like EEG and MEG can provide insights into the dynamics and timing of this neuronal activity and its functional connectivity during resting states. To enhance the analysis of rs-FC, some future directions may include delving further into network connectivity patterns like the DMN and conducting longitudinal studies, as described by Kocher et al., [24] to further elucidate the functional vitality of these neural networks and track alterations over time.

A common trend observed in computational models for the analysis of rs-FC typically involves the use of both machine learning (ML) algorithms [35] and advanced statistical approaches [32]-[33] to extract and analyze rs-FC data. This trend becomes promising due to its capability to effectively process an enormous amount of imaging data associated with rs-FC and identify intricate connectivity patterns that may not be apparent with conventional approaches. Furthermore, the ability of these models to manage high-dimensional data, including connectivity matrices, has enabled a more nuanced knowledge of neural connectivity. However, there are several limitations in terms of capturing the range of rs-FC-influencing variables, such as behavioral, genetic, and environmental factors. The oversimplification of the highly interconnected brain's neural networks by current computational models can lead to a restricted understanding of their true complexity. Furthermore, the requirements for large data sets for model training and validation can be challenging to come by, especially for uncommon or specialized populations. The diversity in rs-FC data between individuals and populations can potentially impede the generalizability of the outcomes. Therefore, the prospects for improving the understanding of rs-FC and the accuracy of the findings might consider the development of progressively convoluted computational frameworks that combine multimodal imaging data (EEG, MEG) and integrate complex network dynamics.

IV. CONCLUSION

This study highlights the significance of multimodal imaging and computational modeling in rs-FC analyses and its effects on cognitive functions. Modalities such as fMRI, fNIRS, EEG, and MEG were determined to be useful in both identifying and providing complementary information about the patterns in the rs-FC and how they relate to cognitive processes. Among all, fMRI emerged to be the most popular imaging approach for rs-FC studies. The key result reveals that increased functional connectivity levels are associated with higher Exin ratios, thereby affecting large-scale functional brain synchronization. Changes in rs-FC, specifically in the connectivity between the medial prefrontal cortex and medial temporal lobe, may impact individual cognitive performance. Outcomes from computational models, on the other hand, indicate that the multivariate model can potentially outperform the univariate classification method with a predictive AUC of ~0.77. Due to its capability to handle multiple EEG features, it has made a non-parametric classifier based on ensembles of decision trees accessible in various contexts. These findings have indeed offered insight into the neural mechanisms that underlie cognitive abilities and demonstrate the importance of leveraging imaging and computational frameworks in studying functional connectivity during resting states.

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