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Original Research

Abnormal Brain Connectivity Patterns in Children with Global Developmental Delay Accompanied by Cognitive Impairment: A Resting-State EEG Study

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Abstract

Background: Global developmental delay (GDD) is a common childhood neurodevelopmental disorder characterized by the core symptoms of cognitive impairment. However, the underlying neural mechanisms of the cognitive impairment remain unclear. This study aimed to both analyze differences in electroencephalography (EEG) connectivity patterns between children with GDD and typical development (TD) using brain functional connectivity and to explore the neural mechanisms linking these differences to cognitive impairment. **Methods**: The study enrolled 60 children with GDD and 60 TD children. GDD participants underwent clinical assessment via the Gesell Developmental Schedule (GDS). Resting-state EEG data were subjected to brain functional connectivity analysis and graph theory metric-based network analysis, with intergroup functional differences compared. Subsequently, correlation analysis characterized the relationships between GDD subject's brain network metrics and GDS-derived cognitive developmental quotient (DQ). Finally, three support vector machine (SVM) models were constructed for GDD classification and feature weight factors were calculated to screen potential EEG biomarkers. **Results**: The two groups exhibited complex differences in functional connectivity. Compared with the TD group, the GDD group showed a large number of increased functional connections in the θ, α, and γ-bands, along with a small number of decreased functional connections in the α and γ-bands (all $p < 0.025$). Brain network analysis revealed lower global efficiency, local efficiency, clustering coefficient and small-world coefficient, as well as higher characteristic path length in GDD children across multiple bands (all $p < 0.05$). Correlation analysis indicated that global efficiency and small-world coefficient in θ and γ-bands were positively correlated with the DQ, while the characteristic path length in α and γ-bands was negatively correlated with DQ in the GDD group (all $p < 0.05$). Machine learning models showed that a quantum particle swarm optimization SVM (QPSO-SVM) achieved the highest classification performance, with characteristic path length in the γ-band being the highest weighted metric. **Conclusions**: Children with GDD exhibit abnormal patterns of brain functional connectivity, characterized by global hypo-connectivity and local hyper-connectivity. Specific network metrics under these abnormal patterns are significantly correlated with cognitive impairment in GDD. This study also highlights the potential of the γ-band characteristic path length as an EEG biomarker for diagnosing GDD.

Keywords: global developmental delay; electroencephalography; functional connectivity; Gesell Developmental Schedules; support vector machines

1. Introduction

Global developmental delay (GDD) is a common childhood neurodevelopmental disorder characterized by core symptoms of cognitive impairment. It is a relatively prevalent birth defect with a poor prognosis, affecting 1–3% of children [1]. The majority of children with GDD progress to intellectual disability by age five, resulting in delayed intellectual, motor and language development, as well as reduced life expectancy, thereby posing significant threats to life and health [2,3].

The etiology of GDD is complex, with multiple factors interacting reciprocally. The heterogeneity of etiologies underscores their intricate neurodevelopmental mechanisms, which remain largely unexplored and pose significant challenges for developing effective interventions. Furthermore, current GDD diagnosis methods rely primarily on clinical symptoms and assessment scales [4], which are highly subjective, casting doubt on the accuracy and reliability of evaluation results. This presents challenges for the early diagnosis of GDD. Thus, exploring objective as-

sessment metrics and identifying potential biomarkers are highly important for early diagnosis and precision intervention in children with GDD.

Network analysis based on neural signals provides a method to address the above issues. The core symptom of children with GDD is cognitive impairment, which leads to structural and functional brain changes, manifested as alterations in the brain network and its parameters [5]. An EEG study exploring brain network change mechanisms in children with perinatal stroke-related cognitive impairment revealed that specific cognitive functions correlate with distinct brain network properties and functional network characteristics after perinatal stroke reflect poorer cognitive function in these children [6]. A quantitative EEG spectral and functional connectivity analysis revealed that patients with Parkinson's disease and mild cognitive impairment exhibited significant alterations in the phase lag index (PLI) in the δ and θ-bands, and these alterations were correlated with cognitive function [7]. Additionally, diffusion tensor imaging (DTI)-based MRI brain functional network analysis revealed that patients with cognitive decline presented with disrupted topological efficiency of brain functional connectivity, specifically decreased global and local efficiency. Reduced rich-club and local connection strengths were found to be associated with impaired memory performance [8]. Another DTI-based brain structural network study revealed that children with GDD and speech delay had significantly lower global and local efficiency than typical development (TD) children, with reduced node strength for cognitive networks in GDD. Such network abnormalities may underlie the common neurocognitive and behavioral consequences in children with global and language developmental delays [5] and is thought to be related to immature brain development [9]. A functional magnetic resonance imaging (fMRI) study by Gozdas *et al*. [10], demonstrated that functional brain network connectivity in preterm infants without anatomical injury was altered compared with that in term infants, potentially serving as an early predictor of cognitive impairment. Functional near-infrared spectroscopy (fNIRS), a noninvasive neuroimaging technique for monitoring cerebral blood flow, is considered closely related to fMRI. Studies have shown significant correlations between hemodynamic responses measured by fNIRS and blood oxygen level-dependent responses obtained by fMRI [11]. A fNIRS study by Zhang *et al*. [12] revealed that reduced functional connectivity strength in the left dorsolateral prefrontal cortex of Alzheimer's disease (AD) patients was positively correlated with the degree of cognitive impairment, suggesting that this is a key affected cortical region. A study using magnetoencephalography technology found that changes in brain functional networks in patients with autism spectrum disorders may be related to epileptic discharges [13]. Despite various biomarker-based monitoring methods, EEG offers portability, high temporal resolution and good motion tolerance [14,15], making it more suitable for studying developing populations [16]. Thus, it holds great potential in identifying cognitive impairment in children with GDD.

The combined application of EEG analysis and machine learning methods represents an active research area in neuroscience and disease diagnosis. Machine learning algorithms extract information from EEG signal features to train models, reducing subjectivity in manual analysis and enabling more objective classification of different brain states or disease diagnoses. Currently, with the widespread application of artificial intelligence, machine learning is undergoing rapid development in the context of neurodevelopmental disorders such as GDD, and is particularly suitable for constructing diagnostic and prognostic models for neurological disorders [17].

In summary, EEG-based brain network analysis has played a significant role in numerous neurological disorders because of its unique advantages. However, few studies have focused on brain network characteristics in children with GDD. The aim of this study was to investigate alterations in brain functional connectivity and network analysis between children with GDD and TD individuals. Here is hypothesized that: (a) Compared with TD children, GDD children exhibit altered EEG functional connectivity featuring a dual pattern of "global hypoconnectivity and local hyperconnectivity"; (b) Brain network metrics across different EEG bands are altered in GDD children, with certain metrics potentially serving as GDD biomarkers. To test these hypotheses, the weighted phase lag index (wPLI) was used across different bands for functional connectivity and brain network topological analysis to explore functional network differences between groups, examine correlations between brain network metrics, clinically obtain cognitive-related scale scores and finally establish a classification model using machine learning to distinguish GDD from TD children and identify potential GDD biomarkers.

2. Materials and Methods

2.1 Participants

Participants included children with GDD (GDD group) and typically developing children (TD group). Inclusion criteria included: (a) Meeting the diagnostic criteria for GDD defined in the Diagnostic and Statistical Manual of Mental Disorders (Fifth Edition) (DSM-5); (b) GDD children showing scores <75 in at least two domains on the Gesell Developmental Schedule (GDS), including the adaptive performance domain most relevant to cognitive development; (c) Being aged 2–5 years, regardless of sex; (d) Provision of written informed consent from parents or guardians. Exclusion criteria included: (a) Children with confirmed genetic metabolic diseases, chromosomal abnormalities, neurodegenerative diseases, or structural brain injuries; (b) Meeting the DSM-5 diagnostic criteria for autism spectrum disorder (ASD), attention-deficit/hyperactivity disorder (ADHD), schizophrenia, etc.; (c) Untreated severe hearing impairment (pure-tone au-

diometry threshold >70 dB) or visual impairment (corrected visual acuity <0.3); and (d) A history of severe infection, craniocerebral trauma, or major surgery within the past six months.

Participants in the GDD group were recruited from the Department of Child Rehabilitation, the Third Affiliated Hospital of Zhengzhou University, Zhengzhou, China. The participants in the TD group were sex- and age-matched and recruited from local kindergartens during the same period. Sample size estimation was performed via G*Power software (Version 3.1.9.7; Heinrich-Heine University, Düsseldorf, Germany), which has a statistical power of 0.95 ($1 - \beta = 0.95$) with an alpha of 0.05 for *t*-tests, resulting in a minimum requirement of 42 participants per group. The study ultimately included 65 GDD and 60 TD participants. However, five participants with GDD were excluded from the subsequent analysis because of their inability to follow instructions and the presence of frequent blinking or muscular artifacts.

This study was conducted at the Third Affiliated Hospital of Zhengzhou University from October 1, 2024 to March 31, 2025. It was approved by the Ethics Committee of the Third Affiliated Hospital of Zhengzhou University. The research was conducted in strict accordance with the Helsinki Declaration. Prior to the study, the research protocol was fully explained to the legal guardians of each participant.

2.2 Clinical Assessment

The developmental status of the participants was assessed via a standardized developmental evaluation tool GDS which was especially for children ranging from 0–6 years of age [18]. The scale determines normal development and identifies delays or abnormalities by observing a child's behavioral performance across multiple domains. Each assessment was independently performed by three trained clinicians who followed protocols for consistency and reliability. The assessment results are expressed as a developmental quotient (DQ), where DQ = (developmental age/chronological age) × 100.

2.3 EEG Acquisition and Preprocessing

Participants sat in a quiet temperature-controlled room for resting-state EEG recordings with their eyes closed. A 32-channel Ag/AgCl scalp electrode system (ZhenTecBci Co., Ltd., Xi'an, China), arranged according to the international 10–20 system, was used, comprising thirty acquisition electrodes and two electrooculography electrodes (horizontal electrooculogram right and horizontal electrooculogram left). The reference electrode was placed at CPz (Central Parietal z) and the ground electrode at FPz (Frontopolar z). Electrode impedance was maintained below 5 kΩ to ensure an optimal signal-to-noise ratio. Signals were amplified and sampled at 500 Hz, with recordings lasting 10 minutes (**Supplementary Material 1** contains detailed channel locations).

EEG data were preprocessed via EEGLAB v14.1.2b (https://eeglab.org) and MATLAB R2021b (https://ww2.mathworks.cn/), involving the following steps: Removal of horizontal electro-oculogram right (HEOR) and horizontal electro-oculogram left (HEOL) electrodes; bandpass filtering (0.1–40 Hz) to reduce noise; manual removal of corrupted data segments, with bad channels replaced by the average of neighboring channels; manual artifact removal; segmentation into two second epochs; independent component analysis to isolate brain activity components, removing those affected by eye movements, muscle activity, or cardiac artifacts; referencing to the average electrode; rejection of segments with significant electromyographic artifacts or extreme amplitudes; with each subject ultimately retaining 90 consecutive two second segments, for a total of 180 seconds of preprocessed EEG data.

2.4 Brain Functional Connectivity and Network Analysis

The brain networks within a 1–40 Hz frequency range were calculated via the HERMES (https://hermes.med.ucm.es/) toolbox, with frequency bands divided into δ (1–4 Hz), θ (4–8 Hz), α (8–12 Hz), β (12–20 Hz) and γ (20–40 Hz) bands. Due to the nonlinear characteristics of EEG signals, phase synchronization-based methods more objectively characterize the interdependencies between channels across different brain regions [19]. The phase locking value (PLV), PLI, and weighted phase lag index (wPLI) describe phase synchronization between two channels: The PLV quantifies the strength of phase synchronization between two signals and reflects the consistency of neural oscillation synchronization between brain regions. However, it is insensitive to volume conduction and may overestimate spurious connections. PLI infers the "causal trend" of information transfer between brain regions through the directional distribution of phase differences between two signals. Its advantage lies in canceling the effect of zero-lag phase differences to reduce volume conduction interference. A study comparing six connectivity assessment methods showed that PLI and PLV had poor classification performance [20]. wPLI, which is based on the PLI, weights and scales phase differences according to their proximity to the real axis, further reduces volume conduction effects while more accurately depicting the "strength and direction" of true functional connectivity [21]. Thus, this study adopted wPLI-based brain networks to investigate the developmental delay mechanisms of participant's brain cognitive functions. When $x(t)$ and $y(t)$ denote the EEG signals from two leads; wPLI is given by:

$$\text{wPLI} = \left| \frac{\sum_{t=1}^{n} |imag\,(S_{xy,t})|\, sgn\,(imag\,(S_{xy,t}))}{\sum_{t=1}^{n} |imag\,(S_{xy,t})|} \right| \quad (1)$$

Where $S_{xy,t}$ is the phase of x(t) and y(t) at time t, and where imag $(S_{xy,t})$ is the imaginary part of the phase difference vector between x(t) and y(t), i.e., sin $(S_{xy,t})$, sgn (imag $(S_{xy,t})$) is the positive or negative sign of

$\sin(S_{xy,t})$, when $\sin(S_{xy,t}) > 0, \mathrm{sgn}(\mathrm{imag}(S_{xy,t})) = 1$; when $\sin(S_{xy,t}) < 0, \mathrm{sgn}(\mathrm{imag}(S_{xy,t})) = -1$.

Currently, the complex network analysis method based on graph theory is widely used to study the interconnection relationships between brain regions. The construction of functional brain networks mainly involves the selection of nodes and edges. In constructing functional networks, electrode positions are regarded as nodes, and the wPLI values between electrodes serve as edges. However, noise and non-feature signals often lead to many weak connection edges in a network. To distinguish the brain region dependency effectively between individuals within GDD and TD groups while maintaining global network connectivity as much as possible, this study used a 40% threshold to capture the topological features of the brain network [22], see **Supplementary Material 1**. Connections below the threshold were set to 0, and connections above the threshold were retained, converting the calculated fully connected brain functional matrix into an undirected weighted thresholded network.

Network-based statistics (NBS) is a method specifically designed for the statistical analysis of brain network/functional connectivity matrices [23]. The MATLAB-based NBS toolbox (https://www.nitrc.org/projects/nbs) was used to identify subnetworks with statistically significant differences in between-group comparisons of brain networks. To better quantify the connection relationships and structural characteristics of functional brain networks, five basic indices of complex networks were selected for quantitative characterization [24], including global efficiency, local efficiency, characteristic path length, the clustering coefficient and the small-world coefficient. Generally, global efficiency characterizes the overall transmission efficiency of parallel information in the network. Local efficiency is used to measure the closeness of connections between a node and its neighboring nodes, reflecting local transmission efficiency. The characteristic path length, the average distance between any two nodes, represents the network's signal transmission capability and describes the efficiency of information transfer within the network. The clustering coefficient refers to the degree to which the neighboring nodes of a given node are interconnected. In brain networks, a high clustering coefficient is typically associated with improved information processing and cognitive abilities [25].

A small-world network is a network structure with efficient information transfer characteristics, whose core features are a high clustering coefficient and short average path length. It is commonly used to describe an intermediate state between regular and random networks. Brain networks achieve a balance between local functional modularity (high clustering) and global integration (short path length) through small-world properties, supporting complex functions such as cognition and memory [26]. The small-world coefficient (σ) is an index for quantifying small-world network characteristics. It is calculated by comparing the clustering coefficient (C) and average path length (L) of an actual network with the corresponding values (C_rand, L_rand) of a random network of the same size: σ = (C/C_rand) / (L/L_rand). A $\sigma > 1$ indicates that the network has small-world characteristics with both high clustering and low path length.

The MATLAB Brain Connectivity Toolbox (BCT, http://www.brain-connectivity-toolbox.net) was used to calculate brain network parameters [27]. These metrics collectively provide insights into the brain network efficiency and information transmission capacity of the two groups of participants.

2.5 Development of Classification Models and Feature Weight Rankings

The support vector machine (SVM), a supervised machine learning algorithm, exhibits unique advantages in binary classification problems. It separates data points of different classes by identifying the optimal hyperplane [28], while enhancing model generalization by maximizing the boundary between classes. In this study, a thematic classification method was used to extract five brain network indicators as features from five frequency bands, and machine learning-based SVM models were developed to evaluate their classification ability for the TD and GDD groups. To optimize model parameters, particle swarm optimization (PSO) and quantum particle swarm optimization (QPSO) algorithms were introduced. These swarm intelligence optimization algorithms search for optimal solutions by simulating collaborative-competitive mechanisms in biological groups: PSO updates on the basis of particle position and velocity iterations, whereas QPSO introduces probabilistic search characteristics from quantum mechanics to enhance the global optimization capability [29]. A 10-fold cross-validation strategy was adopted (90% data for training and 10% for testing per fold), with model performance evaluated across five dimensions: Accuracy, precision, recall, F1 score and area under the receiver operating characteristic curve (AUC) [30].

To determine feature importance, permutation feature importance was used to identify key features [31]. This method measures feature significance by randomly shuffling feature values and observing the degree of decline in model prediction performance. In this study, 100 random permutations were performed to enhance reproducibility and the five most important features were identified and reported, providing data support for mining neurobiological GDD markers. The technical roadmap of this study is given in Fig. 1.

2.6 Statistical Analysis

This study used the statistical and machine learning toolboxes in MATLAB R2021b for statistical analysis. The NBS method was employed to identify subnetworks with significant differences via two-tailed t-tests with a threshold of 2.6 and 50,000 random permutations. The family-

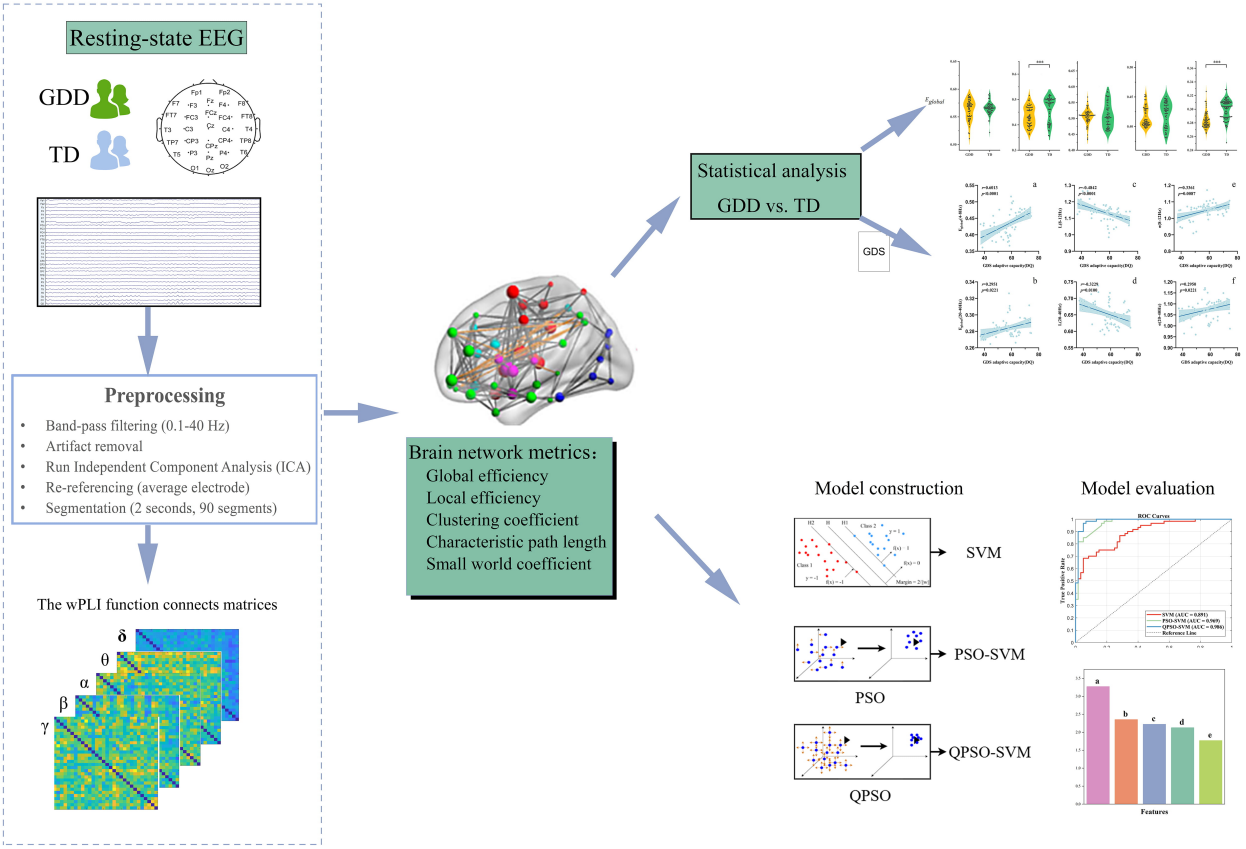

Fig. 1. Technology roadmap. Subfigures (a–f): Correlation between different brain network metrics and adaptive capacity (DQ) in the GDD group; Features (a–e): (a,b) Characteristic path lengths in the γ and α-bands. (c) Clustering coefficients for the γ-band. (d,e) Global efficiency in the γ and β-bands. GDD, global developmental delay group; TD, typically developing group; wPLI, weighted phase lag index; ROC, Receiver operating characteristic; AUC, Area under ROC curve; SVM, support vector machine; PSO, particle swarm optimization; QPSO, quantum particle swarm optimization; GDS, Gesell Developmental Schedule.

wise error rate corrected p-value threshold was set at 0.025. Statistical analysis visualization was performed via GraphPad Prism 9.5.0 (GraphPad Software, Inc., San Diego, CA, USA) (https://www.graphpad.com). Continuous variables are expressed as the mean $\pm$ standard deviation (mean $\pm$ SD), whereas categorical variables are presented as counts. The Kolmogorov–Smirnov test was used to assess the normality of data. For normally distributed data, independent samples t-tests or Welch's t-tests were used to compare between-group differences based on the results of the homogeneity of variance test; for non-normally distributed data, either Mann–Whitney U or Wilcoxon signed-rank tests were applied. Effect sizes were calculated via Cohen's d and Cliff's δ. The false discovery rate (FDR) correction was employed to perform multiple comparison correction on brain network metrics across five frequency bands, all p-values were adjusted for the FDR. To further explore the relationships between brain functional network parameters and clinical scores, Pearson and Spearman linear correlation analyses were conducted to examine the correlations between five brain network features across different bands and GDS social adaptability scores. Statistical significance was set at $p < 0.05$.

Table 1. Demographic characteristics of the subjects.

Demographics	Categories	GDD	TD	Z/χ^2	p-value
Number		60	60		
Sex[a]	Boy/Girl	30/30	35/25	0.838	0.360
Age (year)[b]		2.80 (1.10)	2.80 (1.00)	0.175	0.861
Height (cm)[b]		94.50 (10.70)	97.45 (8.50)	0.347	0.729
Weight (kg)[b]		13.65 (2.90)	13.40 (2.40)	1.397	0.162
Hand[a]	L/R	4/56	2/58	0.174	0.402

GDD, Global developmental delay group; TD, Typically developing group; L/R (left/right); [a] Chi-square test; [b] Rank-sum test.

3. Results

3.1 Demographics and Clinical Characteristics

All the subjects completed the data collection. No significant differences were observed between the two groups of children in terms of sex, age, or handedness (Table 1).

3.2 Differences in Functional Connectivity Strength Between the Two Groups

To compare and analyze functional connectivity strength differences between the two groups of brain net-

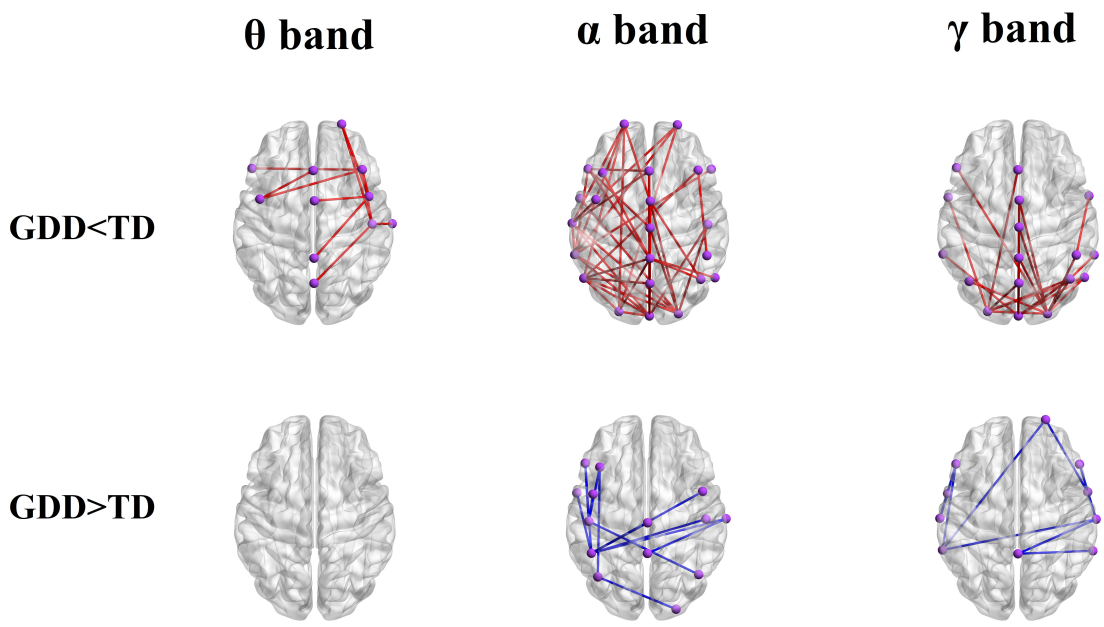

Fig. 2. Comparison of the difference in wPLI connection strength between the GDD and TD groups in different frequency bands. GDD, Global developmental delay group; TD, Typically developing group; GDD < TD, Connection strength of the GDD group is lower than that of the TD group (red line); GDD > TD, Connection strength of the GDD group is greater than that of the TD group (blue line).

works, NBS was employed to identify statistically significant subnetworks, which were then visualized. Results revealed significant differences in brain functional network connectivity between the GDD and TD groups, with the GDD group showing reduced global functional connectivity strength and increased local functional connectivity strength, as given in Fig. 2. Specifically, the local functional connectivity strength across the θ, α and γ-bands in the GDD group was significantly lower than those the TD group. Conversely, in the α and β-bands, the local functional connectivity strength of electrode connections in the GDD group was significantly greater than those in the TD group (details of interelectrode connectivity strength differences are given in **Supplementary Material 1**).

3.3 Differences in Brain Network Metrics

Results of the brain network parameter analysis revealed significant differences in network metrics across the four EEG bands between the GDD and TD groups (Fig. 3). Small-world network analysis revealed that the brain networks of both groups exhibited small-world properties ($\sigma > 1$).

Specifically, in the θ-band, the global efficiency and small-world coefficient in the GDD group were significantly lower ($p < 0.0001$, $\delta = 0.258$; $p < 0.0001$, $\delta = 0.391$), whereas the characteristic path length was significantly greater ($p < 0.0001$, $\delta = 0.356$) than that in the TD group.

In the α-band, the characteristic path length and small-world coefficient in the GDD group were significantly greater ($p < 0.0001$, $\delta = 0.294$; $p = 0.007$, $\delta = 0.195$) than those in the TD group.

In the β-band, the local efficiency and clustering coefficient in the GDD group were significantly lower ($p = 0.0062$, $\delta = 0.238$; $p = 0.0022$, $d = 0.625$, respectively) than those in the TD group.

In the γ-band, the global efficiency, local efficiency, clustering coefficient and small-world coefficient in the GDD group were significantly lower ($p < 0.0001$, $\delta = 0.493$; $p < 0.0001$, $\delta = 0.458$; $p < 0.0001$, $\delta = 0.429$; $p = 0.05$, $d = 0.412$, respectively), whereas the characteristic path length was significantly greater ($p < 0.0001$, $\delta = 0.483$) than those in the TD group.

Supplementary Material 2 gives more detailed statistical results of the brain network parameters.

3.4 Correlation Analysis

To evaluate the relationships between cognitive function and brain network metrics in GDD participants and identify potential biomarkers, the correlations between the five brain network topological metrics and the GDS social adaptation DQ in the GDD group were analyzed. Results revealed significant positive correlations between the global efficiency in the θ and γ-bands and the DQ ($r = 0.6013$, $p < 0.0001$; $r = 0.2951$, $p = 0.0221$, respectively). The characteristic path lengths in the α and γ-bands were significantly negatively correlated with the DQ ($r = -0.4842$, $p < 0.0001$; $r = -0.3229$, $p = 0.0100$, respectively), whereas the small-world coefficients in the θ and γ-bands were significantly positively correlated with the DQ ($r = 0.3361$, $p = 0.0087$; $r = 0.2950$, $p = 0.0221$, Fig. 4).

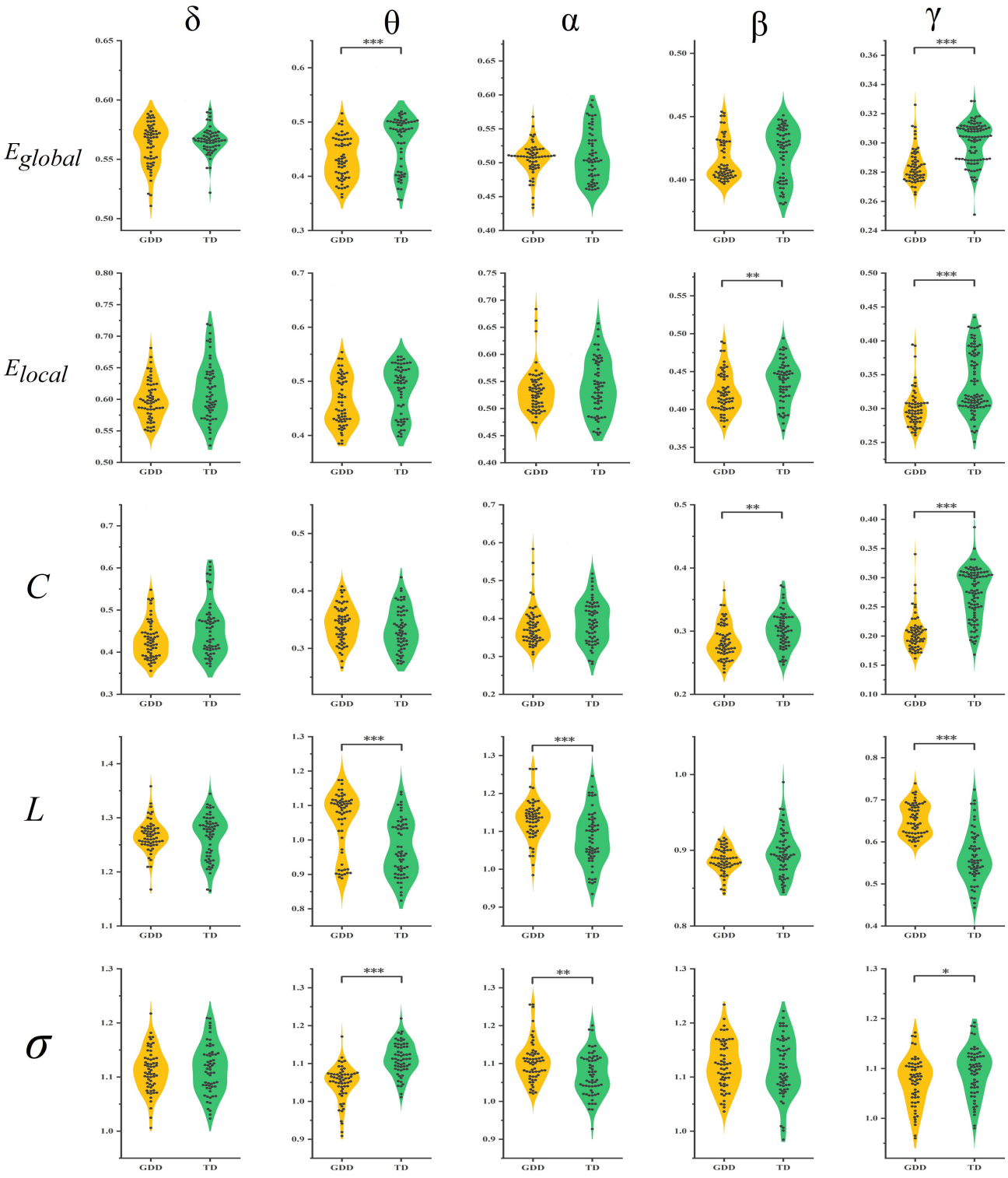

Fig. 3. Comparison of differences in different brain network metrics in different frequency bands between the GDD and TD groups. E_{global}, Global efficiency; E_{local}, Local efficiency; C, Clustering coefficient; L, Characteristic path length; σ, Small-world coefficient; GDD, Global developmental delay group; TD, Typically developing group; *, $p \leq 0.05$; **, $p < 0.01$; ***, $p < 0.001$.

3.5 Classification Models and Feature Weight Rankings Analysis

ROC curves demonstrated that the quantum particle swarm optimization SVM (QPSO-SVM) model achieved the highest AUC value of 0.986, whereas the AUC values for SVM and PSO-SVM were 0.891 and 0.969, respectively, as given in Fig. 5a. Among these models, QPSO-SVM outperforms the others in terms of accuracy, precision, recall, and F1 score (Fig. 5b).

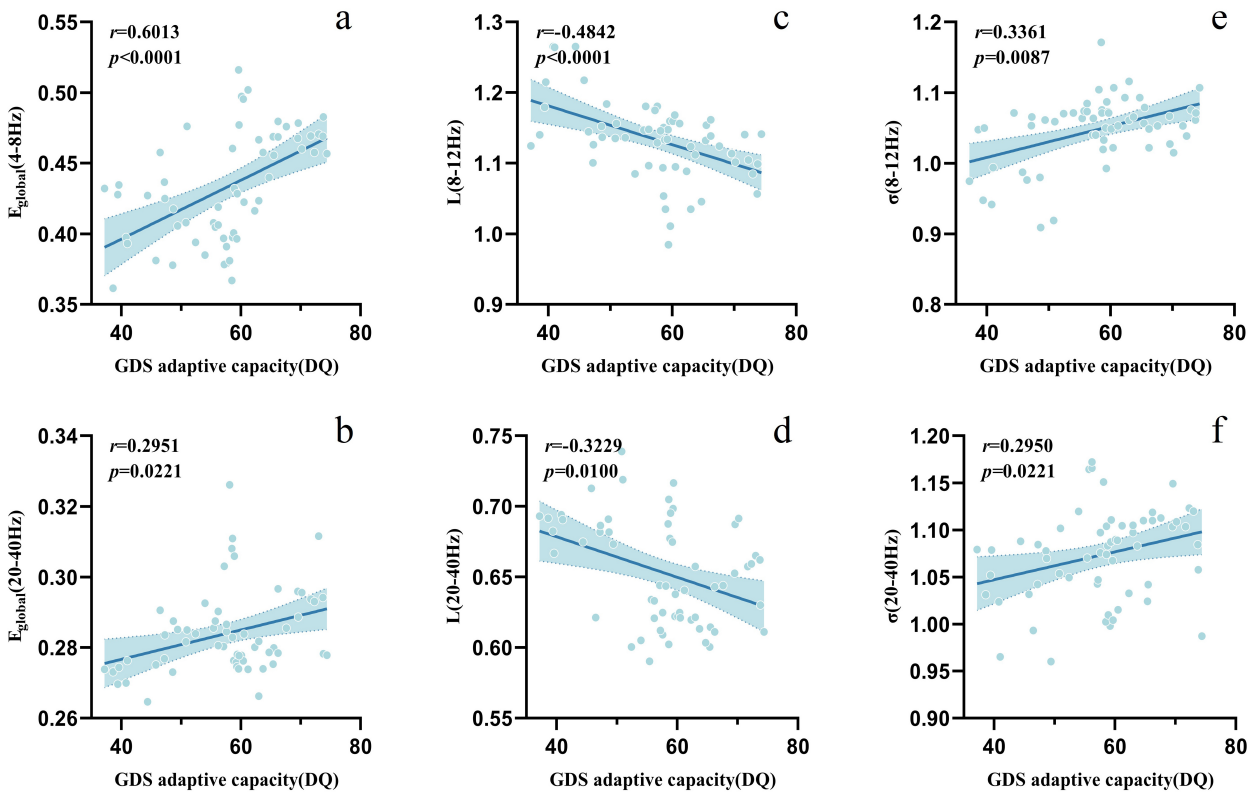

Fig. 4. Correlation analysis between adaptive capacity (DQ) and brain network metrics in the GDD group.

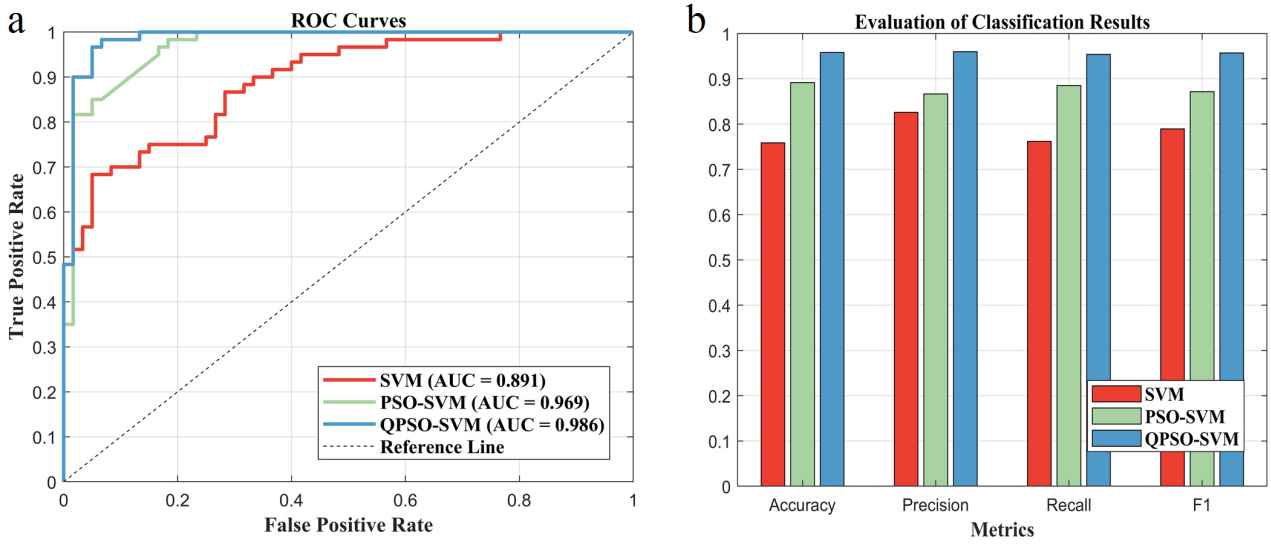

Fig. 5. Evaluating the classification effects of different SVM models. (a) Comparison of ROC curves and AUC values for different classification models. (b) Multi-criteria performance evaluation of different classification models. ROC, Receiver operating characteristic; AUC, Area under ROC curve. The accuracy of the SVM is 0.7417, that of the PSO-SVM is 0.8917 and that of the QPSO-SVM is 0.9583. The precision of the SVM is 0.9189, that of the PSO-SVM is 0.8507, and that of the QPSO-SVM is 0.9508. The recall of the SVM is 0.5667, that of the PSO-SVM is 0.9500, and that of the QPSO-SVM is 0.9667. The F1 of the SVM is 0.7021, that of the PSO-SVM is 0.8978, and that of the QPSO-SVM is 0.9587.

Fig. 6 presents the average feature weights of the top five features across the three models after 100 random permutations, with the characteristic path length in the γ-band exhibiting the highest weight.

4. Discussion

To the best of our knowledge, this is the first study to comprehensively explore whole-brain functional connectivity between GDD and TD participants via EEG and the

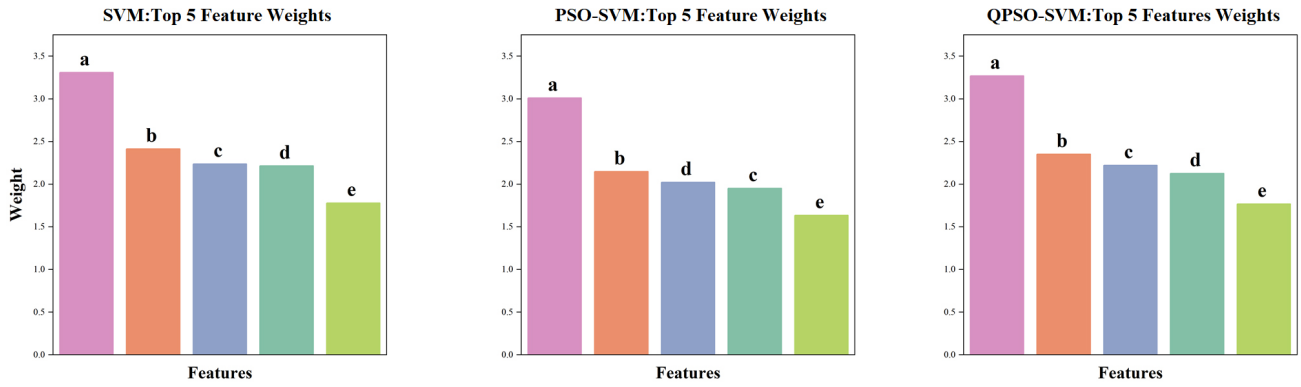

Fig. 6. Top five feature weight rankings of different SVM models. SVM, PSO-SVM and QPSO-SV make the top five average features. The weight ranges of the three models were not normalized. (a,b) Characteristic path lengths in the γ and α-bands. (c) Clustering coefficients for the γ-band. (d,e) Global efficiency in the γ and β-bands.

first to report associations between graph-theoretical network metrics and cognitive impairment in GDD patients. This study basically validated the pre-established hypotheses. Specifically, GDD participants presented significantly weaker connectivity across multiple frequency bands, with enhanced connectivity in specific bands, demonstrating a dual pattern of "global hypoconnectivity and local hyperconnectivity". In terms of brain network metrics, GDD participants presented significantly reduced global efficiency, local efficiency, clustering coefficients and small-world coefficients, as well as extended characteristic path length across multiple bands, when compared to TD participants. Correlation analysis and machine learning results indicated that alterations in brain network parameters across certain bands were significantly associated with cognitive function scores in GDD participants, among which the characteristic path length in the γ-band emerged as a potential biomarker for evaluating GDD and its severity of cognitive impairment. These findings provide a potential objective approach for GDD diagnosis and assessment and offer references for selecting precision therapeutic targets.

4.1 Functional Connectivity and Network Metrics

Functional networks in the human brain typically exhibit high levels of segregation and integration to enhance local and global information processing efficiency [32]. EEG functional connectivity analysis, by quantifying the synchronization of electrical signals across different brain regions reveal spontaneous coordinated activities within intrinsic networks such as the default mode network (DMN), reflecting the brain's modular organization and information integration capabilities. Graph-theory-based brain network analysis enables a comprehensive exploration of alterations in GDD brain functional connectivity at a higher level of network organization. In the following sections, the differences in brain functional connectivity and network analysis metrics between the two groups of participants across different frequency bands are discussed, as are the underlying neural mechanisms.

δ-Band: In the resting state, the δ-band primarily reflects cortical metabolic activity and spontaneous synchrony of the DMN [33]. This study did not find significant differences between the two groups of participants in terms of brain connectivity and network metrics. This is inconsistent with the results of a previous study on ADHD brain networks, which reported reduced δ-band network connectivity in ADHD patients [34], providing different insights into the study of these two neurodevelopmental disorders. Notably, even without statistical significance, the results revealed a trend toward greater average global efficiency in the GDD group than in the TD group. It is thus reasonably speculated that GDD participants may compensate for local deficits through long-range connections (e.g., cross-network connectivity between the DMN and dorsal attention network) to maintain overall brain function stability [35]. This compensatory mechanism has also been observed in patients with schizophrenia [36].

θ-Band: The θ-band is associated with memory encoding, DMN function and cortical integration [37]. Results given here showed that the connectivity strength of multiple cross-brain region connections in the α-band was significantly lower in the GDD group than in the TD group, indicating that GDD participants have lower resting interregional information integration and transmission efficiency. This finding is consistent with a previous study on ASD [38]. Given that ASD and GDD are both neurodevelopmental disorders sharing similar etiologies, clinical manifestations, and imaging features [39,40]. This study enriches the understanding of brain functional network changes in these two conditions and suggests shared neuroelectrophysiological mechanisms. Network analysis shows that the GDD group has lower global efficiency but longer characteristic path lengths than the TD group, indicating that GDD participants may have lower global information transmission efficiency and longer information transmission paths, leading to an imbalance in cognitive resource allocation. Notably, although the small-world coefficients of both groups were greater than unity, those of the GDD group were lower

than those of the TD group, suggesting that while both networks exhibited small-world properties (high clustering and short path length), the optimized "high clustering–short path" structure in GDD brains was disrupted, trending toward randomization. This imbalance between local information integration and global transmission efficiency may underlie cognitive deficits in individuals with GDD.

α-Band: The α-band often reflects the ability of the brain to integrate information [41]. The findings reported here revealed complex differences in functional connectivity strength between the two groups. The study found complex differences in functional connectivity strength between the two groups. When compared to the TD group, GDD participants had a large number of weak connections and fewer high-functioning connections. A previous study reported that α waves are prominent in infancy and gradually change with brain maturation [42], whereas GDD participants may exhibit complex abnormal patterns of α-band functional connectivity due to neurodevelopmental delay. However, the study was unable to localize the functionally impaired brain regions precisely and future studies should use high-density EEG devices for source localization analysis. Additionally, the GDD group presented a significantly longer characteristic path length in the α-band than the TD group did, indicating prolonged information transmission pathways and reduced efficiency. Notably, although not statistically significant, the GDD group presented lower mean global and local efficiency than the TD group did, implying potential impairment in network integration. Contrary to the hypothesis, the GDD group had a significantly higher small-world coefficient in this band, a finding also reported in a study on ASD participants, which revealed increased small-world coefficients in severely affected ASD participants when compared to mildly/moderately affected participants [43]. Considering that both disorders are neurodevelopmental disabilities, further research is warranted to explore their potentially shared neural mechanisms.

β-Band: The β-band is considered to be closely related to cognitive control and sensory movement [44,45]. However, this study did not find significant differences in brain connectivity between the two groups. In terms of brain network metrics, the GDD group had significantly lower local efficiency and clustering coefficient in the β-band than the TD group, which may indicate impaired functional integration of local brain regions. This finding aligns with EEG studies on ASD [46], ADHD [34] and healthy populations [47], which have validated the correlation between reduced β-band functional connectivity and cognitive functions across different subject groups. It is worth noting that this study did not find significant differences between the two groups in terms of feature path length in the β-band. A previous study on autism spectrum disorder (ASD) found that patients had reduced feature path length in the β-band [48] and some researchers have suggested that this may reflect a compensatory effect of local overconnectivity within specific modules on global efficiency decline [49]. However, a different view holds that the shortening of characteristic path length, which is often accompanied by network randomization, may be related to reduced cognitive flexibility [50], highlighting the need to explore the neural mechanisms behind changes in network metrics in depth.

γ-Band: Human γ-band activity has been related to a variety of functions ranging from perception and attention to memory and consciousness [51]. Results reported here demonstrated complex differences in local functional connectivity strength within the γ-band between the two groups. Such complexity may be linked to the theory of insufficient and excessive synaptic pruning, which posits that synaptic pruning is a critical process in brain development—synapses used frequently are retained, whereas idle ones are eliminated [52]. GDD participants may fail to efficiently clear redundant synapses due to developmental disorders while excessively eliminating frequently used synapses, leading to abnormal local functional connectivity and reduced information processing efficiency—a mechanism widely accepted in other neurodevelopmental disorders [53,54]. Langer *et al*. [55] analysed the correlation between brain network parameters and scores on Raven's Standard Progressive Matrices via high-density EEG data and reported that the smarter the subjects were, the more their functional brain networks resembled small-world networks. This finding reveals that efficiently organized resting-state functional brain networks form the basis of high-efficiency cognition. Results further revealed that the GDD group had significantly lower global efficiency, local efficiency, clustering coefficient and small-world coefficient but longer characteristic path length than the TD group, indicating decreased information transmission efficiency and impaired functional integration in GDD participants. The efficient small-world properties of brain networks were disrupted, with networks trending toward randomization. This is consistent with the findings of Jeong *et al*. [5] from DTI data. Additionally, studies using fNIRS have reported similar results in individuals with autism ASD [56] and ADHD [57].

Findings across the five frequency bands validated the pre-established hypothesis tested here: GDD participants presented reduced functional connectivity in three bands (θ, α, γ), alongside local hyperconnectivity in the α and β-bands, demonstrating a dual pattern of "global hypoconnectivity and local hyperconnectivity". The enhanced local connectivity may represent a compensatory response to core deficits such as insufficient information integration, whereas weakened global connectivity directly reflects cognitive impairment. Differences in brain network metrics between groups provide comprehensive insight into abnormal connectivity patterns in GDD participants. However, owing to the high heterogeneity of GDD populations, inherent neural signatures of specific GDD symptoms may be overlooked. These findings highlight the importance of considering clinical heterogeneity in GDD and the neces-

sity of tailored intervention strategies. Future studies could integrate multimodal techniques (e.g., high-density EEG, fMRI, fNIRS) to further analyze the structure–function connectivity correspondence in the brain.

4.2 Correlation Analysis

Correlation analysis revealed that brain network parameters in GDD participants were closely associated with cognitive functions. Specifically, in GDD participants cognitive function was positively correlated with global efficiency in the θ and γ-bands and negatively correlated with characteristic path length in the α and γ-bands. These findings indicate that decreased global efficiency and prolonged path length in specific bands may be closely linked to cognitive decline in GDD participants. The positive correlations between cognitive function and small-world coefficients in the θ and γ-bands suggest that cognitive impairment in GDD participants may be associated with the transformation of small-world networks toward random networks. These findings highlight the clinical importance of these network metrics, which hold promise as objective neurobiological markers for evaluating the severity of GDD and associated cognitive impairments. Moreover, these correlations deepen understanding of the neuropathological mechanisms underlying GDD, providing valuable intervention targets for precision neuroregulatory therapies.

4.3 Prediction Models

SVM, which is rooted in statistical learning theory, achieves structural risk minimization and serves as a supervised learning technique for classification and regression [58]. It has been widely applied to construct clinical disease classification models. Among the three models, the QPSO-SVM model demonstrated the best classification performance. However, its high AUC value suggests a risk of overfitting, which may be related to the small sample size in this study and may affect model generalization to new data. In the future, sample size should be expanded and multi-centre external validation should be conducted to mitigate the impact of such overfitting. Repeated permutations of feature parameters to observe model performance help highlight the contribution of features to model prediction, thereby screening valuable biomarkers. Results show that the characteristic path length in the γ-band had the highest feature weight across all models examined, underscoring its potential as a neural marker. Notably, statistical correlations do not guarantee direct biological mechanisms, necessitating further biological validation to determine their clinical significance.

4.4 Limitations

This study has several limitations. First, the sample size was relatively small, making subgroup analysis on the basis of the severity of cognitive impairment difficult. Future studies could enroll larger samples from multiple centers to better understand the heterogeneity among GDD populations. Second, the heterogeneity of GDD etiologies and the high noise in participant's EEG data limited the choice of sliding thresholds when constructing functional brain networks. Stratified analysis or collection of fNIRS/MRI data with higher SNRs could support range threshold analysis in the future. Finally, the cross-sectional design of this study does not allow the inferring of causal relationships or unraveling the associations between cognitive-behavioral assessments and functional connectivity in GDD participants. Prospective designs are recommended for future research on this topic.

5. Conclusions

This study, which is based on resting-state brain network analysis of EEGs and machine learning algorithms, demonstrated that GDD participants exhibit an abnormal connectivity pattern characterized by "global hypoconnectivity and local hyperconnectivity". It also reveals correlations between brain network parameters in specific frequency bands and cognitive functions in GDD, where the characteristic path length in the γ-band may serve as a promising objective biomarker for GDD diagnosis. These findings provide a novel approach for the objective assessment of cognitive functions in GDD patients and offer references for precision neuroregulatory therapies.

Availability of Data and Materials

The datasets used and analyzed in the present study are available upon request from the corresponding author.

Author Contributions

Conceptualization: ZH, YZ, DZ and YH. Methodology: YH, ZH, YZ, and DZ. Software: ZH, YZ. Validation: ZH and YH. Formal analysis: ZH. Investigation: YS, JK, WQ, YY, LY, GC, SaL, GZ, MW. Resources: DZ, YH. Data Curation: ZH, ShL, JZ, KS. Writing—Original Draft: ZH, YZ. Writing—Review & editing: DZ, YH. Visualization: ZH, YZ, DZ. Supervision: DZ and YH. Project administration: DZ and YH. Funding acquisition: DZ and YH. All authors contributed to editorial changes in the manuscript. All authors read and approved the final manuscript. All authors have participated sufficiently in the work and agreed to be accountable for all aspects of the work.

Ethics Approval and Consent to Participate

The study was conducted in accordance with the Declaration of Helsinki. The research protocol was approved by the Ethics Committee of the Third Affiliated Hospital of Zhengzhou University (Ethic Approval Number: 2024-268-02). All of the participants provided signed informed consent.

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Conflict of Interest

The authors declare no conflict of interest.

Declaration of AI and AI-Assisted Technologies in the Writing Process

During the preparation of this work the authors used DeepSeek (https://www.deepseek.com/) in order to check spell and grammar. After using this tool, the authors reviewed and edited the content as needed and takes full responsibility for the content of the publication.

Supplementary Material

Supplementary material associated with this article can be found, in the online version, at https://doi.org/10.31083/JIN44410.

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