Open Access of High-Density Resting-State EEG Data: Current Status, Challenges, and Prospects

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Abstract

This study systematically analyzes the fundamental status quo, typical applications, and future prospects of open-access high-density resting-state EEG data. Resting-state EEG is extensively utilized due to its straightforward experimental procedures, low cost, non-invasive nature, and high temporal resolution. Currently, internationally shared datasets predominantly originate from Europe and North America, focusing primarily on healthy young and middle-aged populations. These datasets have played a crucial role in both basic research and clinical applications, including neurodevelopmental studies and psychiatric disorder identification, and have yielded significant achievements in biomarker research for mental illnesses. Nevertheless, existing databases exhibit limitations in terms of geographical distribution, population diversity, acquisition protocols, and cohort development. Moving forward, it is imperative to expand sample coverage, conduct longitudinal cohort studies with multiple time points and multi-modal physiological and psychological measures, develop analytical tools for multi-center large-scale datasets, fully integrate artificial intelligence technologies, and adhere to the FAIR principles—ensuring data are Findable, Accessible, Interoperable, and Reusable. Open access to high-density resting-state EEG data will provide robust support for the precise evaluation of brain function.

Full Text

High-Density Resting-State EEG Open-Access Data: Current Status, Challenges, and Future Perspectives

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Abstract

This study systematically examines the current landscape, typical applications, and future prospects of open-access high-density resting-state electroencephalography (EEG) data. Resting-state EEG is widely utilized due to its experimental simplicity, cost-effectiveness, noninvasiveness, and high temporal resolution. Currently, most internationally shared datasets originate from Europe and North America, primarily comprising healthy young and middle-aged populations. These datasets have significantly contributed to both fundamental research and clinical applications, with notable achievements in biomarker discovery for mental illnesses. However, existing databases exhibit limitations in geographic diversity, population coverage, acquisition protocols, and longitudinal cohort design. Future efforts should focus on expanding sample diversity, conducting longitudinal studies with multimodal psychophysiological assessments, developing multicenter large-scale data processing tools, integrating artificial intelligence techniques, and adhering to FAIR (Findable, Accessible, Interoperable, and Reusable) data-sharing principles. Open-access high-density resting-state EEG will provide robust data support for precise brain function evaluation.

Keywords: resting-state EEG, open access, high-density EEG, database, FAIR principle

In recent years, brain functional activity during non-task resting states has garnered widespread attention in neuroscience. This so-called "resting-state" paradigm is believed to reflect intrinsic brain activity and provides information about how different brain regions coordinate their operations [?, ?]. It distinguishes spontaneous neural activity from task-evoked responses, and substantial evidence indicates that these activities can be used to quantify behavior, reflect cognitive functions, and identify diseases [?, ?]. Resting-state brain imaging can be implemented through various techniques. Electroencephalography (EEG) is a non-invasive technique for recording scalp electrical potential fluctuations [?, ?], offering high temporal resolution and cost-effectiveness while providing millisecond-level insights into brain dynamics [?, ?]. Resting-state EEG (rsEEG) represents a specific application of EEG, defined as recordings obtained when participants are not actively engaged in sensory processing or cognitive activity [?, ?]. It provides a window into spontaneous neural oscillations and reflects the brain's intrinsic connectivity and functional architecture. Recent research has primarily focused on analyzing specific frequency bands: δ (1–4 Hz), (4–7 Hz), α (8–12 Hz), β (12–28 Hz), and γ (>30 Hz), each associated with distinct cognitive and behavioral functions [?, ?]. A key advantage of EEG lies in its high temporal resolution, enabling precise capture of rapid cognitive and perceptual processes [?, ?]. Additionally, EEG can be recorded across various environments, enhancing the ecological validity of brain activity measurements [?, ?]. Moreover, EEG's non-invasive nature and low cost make it applicable to populations of all ages and suitable for diverse usage scenarios [?, ?].

This paper defines high-density EEG as recordings with more than 60 electrodes; otherwise, it is considered low-density EEG. Significant differences exist in analytical performance between high- and low-density EEG. Low-density EEG only enables simple network feature analysis and performs poorly on complex network characteristics [?, ?]. Furthermore, high-density EEG systems with 60 or more electrodes substantially improve source localization accuracy [?, ?], while systems exceeding 100 electrodes significantly reduce source localization errors, enabling precise localization of epileptic foci [?, ?, ?]. Previous research has found that when the number of electrodes exceeds 60, the gain in spatial resolution plateaus [?, ?]. Meanwhile, ultra-high-density EEG (>256 channels) faces technical bottlenecks, such as local short circuits caused by physiological saline and electrode paste between adjacent electrodes. Even for experienced technicians, ultra-high-density EEG preparation requires one hour, increasing time costs [?, ?]. Future advances in dry electrodes and microneedle electrodes are expected to substantially reduce preparation time while achieving significant improvements in data quality and comfort.

This paper focuses on the open-access status of high-density resting-state EEG. First, we introduce the subject characteristics and geographic distribution of existing databases. Second, we summarize fundamental features including experimental protocols and analysis techniques. Third, we provide a detailed analysis of current primary research fields and applications for high-density EEG. Finally, we outline recommended pipelines, major methods, and common tools for resting-state EEG analysis, and offer perspectives on future open-access initiatives for high-density resting-state EEG.

2.1 Comparison Between Resting-State EEG and Other Modalities

Resting-state brain imaging can be implemented through multiple technologies. Functional Magnetic Resonance Imaging (fMRI) is a neuroimaging technique that measures and maps brain activity by detecting blood flow-related changes, relying on Blood-Oxygen-Level-Dependent (BOLD) signals suitable for studying correspondences between brain anatomy and functional activity [?, ?]. Researchers have observed spontaneous low-frequency fluctuations in BOLD signals through resting-state fMRI (rs-fMRI), revealing temporal correlation patterns of activity between anatomically separated brain regions and identifying large-scale brain networks including the default mode network and frontoparietal attention network [?, ?]. Magnetoencephalography (MEG) captures weak magnetic fields (on the order of 100 fT) generated by the brain through high-sensitivity magnetic sensors distributed across the scalp surface, enabling non-invasive real-time monitoring of cortical and subcortical activity patterns and widely applied for detecting rapid neural signals from deep brain structures [?, ?]. Functional Near-Infrared Spectroscopy (fNIRS) utilizes the strong scattering properties of blood components to near-infrared light to measure hemodynamic changes in cerebral cortex induced by neural activity, often used for long-term recordings of specific populations in naturalistic environments

[?, ?]. Positron Emission Tomography (PET) can non-invasively examine cerebral blood flow, metabolism, and receptor binding, most commonly used for studying long-term stable metabolic processes and neurotransmitter systems in the brain [?, ?].

In comparison, although fMRI offers high spatial resolution, it only indirectly reflects neural activity and has low temporal resolution. PET and fNIRS suffer from similar temporal limitations. Most cognitive processing occurs on millisecond-to-second timescales, which are better suited for EEG and MEG [?, ?]. Since brain magnetic signals are extremely weak compared to Earth's magnetic field and external electromagnetic interference, MEG requires superconducting technology and strong magnetic shielding, making it prohibitively expensive and far less accessible than EEG. EEG's high temporal resolution, relatively low cost, simple operation, and portability have established it as one of the most commonly used research tools in cognitive neuroscience, covering cognitive function research and clinical disease diagnosis with high 普及率. However, EEG also has limitations, including relatively low spatial resolution, susceptibility to artifacts from external noise and ocular/muscular activity, and inability to reflect signals from deep brain structures, requiring researchers to evaluate its research value dialectically.

2.2 Test-Retest Reliability of Resting-State EEG Metrics

Investigating cognitive neural mechanisms based on scalp EEG signals requires good test-retest reliability. The most commonly used statistic for assessing test-retest reliability is the intra-class correlation coefficient (ICC), defined as the ratio of variance from repeated testing to total variance. Overall, EEG signals demonstrate high test-retest reliability, with ICC values for eyes-closed resting state higher than eyes-open state, and resting-state EEG generally showing higher ICC than event-related potentials (ERP) [?, ?, ?]. The α band in resting state shows high reliability in both eyes-open and eyes-closed conditions, while simple cognitive tasks in ERP, such as the psychomotor vigilance test (PVT), exhibit high test-retest reliability. Ding et al. (2022) found that the test-retest stability of large-scale brain networks is affected by individual state, with reliability for mental imagery tasks lower than that of resting state.

In recent years, aperiodic analysis of resting-state EEG spectra has gained significant attention, with studies demonstrating good test-retest reliability for aperiodic activity (ICC $>$ 0.50; Li et al., 2024), though reliability in task states varies with task type. These psychometric property assessments reflect the potential of resting-state EEG metrics as stable biomarkers.

2.3 Literature Review on Resting-State EEG

We reviewed studies published since 2000, searching the Web of Science database for relevant literature through December 31, 2024. The search was limited to the Web of Science Core Collection, using the following keyword combinations for resting-state EEG retrieval: ((TS=(resting state EEG)) OR TS=(resting state Electroencephalography)) OR TS=(resting state Electroencephalogram). To investigate EEG open-access status, we selected *Scientific Data*, a journal primarily publishing research on scientific data sharing and reuse, and counted annual EEG-related publications from 2000 to 2024 (see Figure 1 [Figure 1: see original paper]).

The publication trend for resting-state EEG shows steady growth from 2000 to 2024. The annual publication count for EEG in *Scientific Data* has surged since the proposal of FAIR (Findable, Accessible, Interoperable, and Reusable) principles in 2014, reflecting researchers' enthusiastic response to open science. Overall, research interest in resting-state EEG has significantly increased in recent years.

3 Overview of Public High-Density Resting-State EEG Databases

Through web searches, we identified 30 publicly available resting-state EEG databases with more than 60 channels, collected from awake participants in a resting state, as of December 31, 2024 (see Table 1).

Table 1 Existing public databases of high-density resting-state EEG

Database Name	Resting-State EEG Experimental Parameters	Country	Modality	Subject Count	Eyes State	Notes
[Multiple database entries with various parameters]						

3.1 Geographic Distribution

Among these datasets, databases from Europe and the United States account for 73% (22 datasets), while datasets from other regions are scarce. Notably, Africa lacks datasets meeting these standards. Specifically, the only locally collected and shared dataset from Africa is the Nigerian Schizophrenia EEG Dataset (NSzED; Olateju et al., 2023), which aims to address the shortage of high-quality EEG datasets from developing and underdeveloped regions by collecting task and resting-state EEG data from schizophrenia patients and healthy controls, though it uses only 18 channels. Brain datasets from low- and middle-income African countries remain relatively scarce (de Aguiar Neto & Rosa, 2019). This demonstrates severe imbalance in racial representation across continents, limiting the generalizability of research findings. Current international experimental research faces the widespread problem of over-reliance on so-called WEIRD (Western, Educated, Industrialized, Rich, and Democratic) samples—participants primarily from Western, educated, industrialized, wealthy, and democratic countries (Jones, 2010). Given EEG's advantages of low cost, portability, and simple operation, high-density EEG is expected to achieve broader population coverage in the future.

3.2 Subject Characteristics

Resting-state EEG data covers all age groups from infants to elderly, with young and middle-aged adults (18–35 years) as the main focus (see Figure 2 [Figure 2: see original paper]). For infants and toddlers, due to small head circumference, datasets typically use around 30 channels. Subject types include both healthy participants and various patient populations. This diversity not only promotes understanding of brain function differences between health and disease states but also advances personalized and precision medicine.

Currently, most data are cross-sectional from single time points. Only four databases include 2–3 longitudinal follow-up sessions. However, for fundamental research, particularly neurodevelopment, multiple time points are needed to characterize brain development, maturation, and aging across the lifespan. Limited sample sizes and acquisition sessions restrict the generalizability of neurodevelopmental research and hinder the discovery of universal developmental principles. For clinical research, insufficient patient data limits exploration of disease pathophysiology and reduces the likelihood of discovering biomarkers, consequently affecting early diagnosis and intervention strategies.

Figure 2 Composition of instruction types, age, and sample size in existing public high-density resting-state EEG databases. Numbers beside the illustration represent database IDs from Table 1, with circle radius linearly scaled to sample size.

3.3 Data Types

Most databases contain multimodal brain imaging information along with other physiological or behavioral data. For example, the Leipzig Mind-Brain-Body Database (Babayan et al., 2019) provides rich multimodal data covering cognition, emotion, and physiology. Multimodal data are crucial for deeply understanding brain function-structure relationships, as different modalities offer complementary spatiotemporal precision, and their integration can improve disease diagnostic accuracy and treatment efficacy assessment (雷旭, 尧德中, 2014). However, multimodal data also present processing and analytical challenges, requiring researchers to possess interdisciplinary knowledge and technical expertise.

3.4 Database Application Status

In this paper, some datasets were released by author teams as original research data, and we also consider experimental papers based on these datasets as database introduction articles. Among the 30 EEG databases analyzed, 25 have published database introduction articles (83% of total databases). These databases with introduction articles have an average citation count of 326, while some databases without introduction articles remain uncited. This significant difference demonstrates that publishing database introduction articles substantially enhances database citation rates.

To improve EEG database citation rates, we recommend that researchers simultaneously publish database introduction articles when releasing databases to facilitate better promotion. Long-term maintenance and updates are also key factors for enhancing citation rates. As more high-quality databases become available and introduction articles are published, we anticipate more influential research outcomes.

4 Typical Applications of Public Resting-State EEG Data

Since some published studies do not meet our requirements for resting-state or >60-channel recordings, we broadly discuss typical applications of public databases.

4.1 Applications in Sleep-Wake Mechanisms

Multiple databases currently exist for investigating sleep-wake mechanisms, which can be used not only to study sleep deprivation effects on cognitive function but also to explore neural mechanisms of sleep and wakefulness. Zhang et al. (2023) found that individuals with lower prefrontal gamma power in resting-state EEG showed increased reactive aggression after sleep deprivation, suggesting that resting-state EEG may serve as a potential biomarker for predicting aggressive behavior following sleep loss.

Several public polysomnography (PSG) databases are available, such as the Montreal Archive of Sleep Studies (O'reilly et al., 2014), with some data simultaneously acquired with fMRI (Sterpenich et al., 2021). However, these databases typically use only 8 electrodes and were not included in our analysis. Future research could combine high-density resting-state EEG with PSG to investigate sleep-wake mechanisms.

4.2 Applications in Neurodevelopment

Due to its accommodative nature for cross-age recordings, resting-state EEG enables the establishment of lifespan databases from infancy, childhood, and adolescence through adulthood to healthy aging, facilitating scientific understanding of brain development across the entire lifespan. With public databases, researchers can access large-scale resting-state EEG data, which is crucial for investigating neurodevelopmental patterns in health and disease. For example, using the Cuban Human Brain Mapping Database, researchers discovered that EEG connectivity changes during infant brain maturation synchronize with synaptogenesis, myelination, and early right hemisphere dominance (Bosch-Bayard et al., 2022). Utilizing large-scale multimodal datasets of brain information processing during development, studies found that multimodal network properties can effectively identify normal developmental states and mental disorders at specific ages, providing reliable approaches for assessing brain age and diagnosing developmental mental health issues (Jiang et al., 2024).

4.3 Applications in Neuropsychiatric Disorders

Resting-state EEG is primarily applied in clinical research to identify biomarkers for neuropsychiatric disorders, including Alzheimer's disease (Meghdadi et al., 2021), autism (Heunis et al., 2016), depression (Sun et al., 2023), insomnia (Shi et al., 2024), and epilepsy (Cecchetti et al., 2021). Large databases such as the National Database for Autism Research (NDAR) provide resources for investigating disease-related neural oscillations. Through mining resting-state EEG signals, researchers found that middle-aged healthy individuals carrying APOE and PICALM risk alleles exhibit EEG "slowing," reduced signal complexity, and altered functional connectivity, potentially indicating future Alzheimer's disease risk (Dzianok et al., 2025). For early autism diagnosis, Huberty et al. (2021) analyzed shared EEG data from 432 participants in the International Infant EEG Integration Platform, finding that autism family risk could predict initial levels and developmental trends of EEG spectral power. Analyzing brain health indicators from the Leipzig Mind-Brain-Body Database, researchers found these indicators could suggest epilepsy likelihood and help lateralize seizure foci even in the absence of recognized epileptiform activity, improving diagnostic success rates (Varatharajah et al., 2020). Using existing shared datasets, researchers have constructed disease classification or prediction models based on EEG signals (Kabbara et al., 2022). Tang et al. (2024) utilized the public ABC-CT resting-state EEG dataset to establish diagnostic models with over 85% accuracy in both single-subject and cross-subject experiments. Other researchers proposed a Deep Ensemble Learning (DEL) model for Alzheimer's disease diagnosis based on two shared 19-channel EEG datasets (Dataset A&B), achieving 97.9% average accuracy in AD classification (Nour et al., 2024). These findings not only provide new perspectives for neuropsychiatric disorder diagnosis but also offer scientific foundations for developing novel diagnostic tools and interventions.

Using microstate analysis to extract information from EEG signals, researchers found significant differences in microstate characteristics between pre- and post-treatment in depression patients. Microstate C correlates with depression severity, while microstates D and E may serve as biomarkers for predicting repetitive transcranial magnetic stimulation treatment response. Abnormal microstate B in visual networks may alter spatiotemporal brain network dynamics in depression and insomnia patients. These findings suggest EEG microstates could become key neurobiological indicators for distinguishing depression from insomnia (Cao et al., 2024).

5.1 Resting-State EEG Analysis Methods

Raw EEG data contain neural electrical activity, physiological artifacts, and non-physiological noise, requiring preprocessing to improve signal-to-noise ratio. Resting-state EEG preprocessing typically consists of: signal denoising, artifact removal, baseline correction, re-referencing, sampling rate adjustment, bad channel/segment rejection, and signal decomposition (Shoka et al., 2019). Preprocessing steps and order are usually determined by study design and data characteristics (Martinek et al., 2021). Traditional preprocessing methods rely heavily on manual inspection, demanding substantial researcher experience, time costs, and yielding subjective results.

Numerous standardized preprocessing pipelines and open-source toolboxes now provide new approaches for large-scale EEG data processing. Distributed computing frameworks significantly improve processing efficiency by distributing data and computational tasks across multiple nodes. Standardized pipelines reduce biases from data processing variations. Consequently, various open-source toolkits and batch processing pipelines have emerged to meet demands for transparency, open access, and big data processing.

The PREP pipeline is a standardized preprocessing method for resting-state EEG data that removes noise through multi-window spectral decomposition, avoiding signal distortion from traditional bandstop filters. By detecting and interpolating artifacts, it progressively estimates true signals, significantly reducing contamination from noisy channels. PREP divides processing into multiple stages, each fully utilizing parallel computing resources while supporting distributed computing (Bigdely-Shamlo et al., 2015). Automagic is an open-source MATLAB toolbox for standardized preprocessing of resting-state EEG data, integrating multiple existing methods such as bad channel detection, filtering, and ICA, while advocating quality assessment metrics based on absolute signal intensity. It also supports management of dynamically growing research data, enabling continuous tracking of preprocessed datasets and maintaining fixed settings as data accumulate, thus accommodating long-term, large-scale, standardized distributed processing needs (Pedroni et al., 2019). DISCOVER-EEG is another automated preprocessing tool that calls EEGLAB and FieldTrip toolboxes to extract and visualize brain functional features (Gil Ávila et al., 2023). Open-source toolkits with automated batch processing capabilities facilitate integration, reuse, and analysis of large EEG datasets, helping researchers build efficient, flexible, and practical workflows for effective large-scale data mining.

Resting-state EEG analysis methods are diverse, covering time domain, frequency domain, time-frequency domain, and complex networks. Time-domain analyses such as amplitude analysis and peak detection quantify psychological processes by directly extracting waveform features, offering simplicity and strong interpretability. Frequency-domain analysis primarily involves power spectral analysis, transforming time-domain signals into frequency-domain spectra to reveal EEG rhythm distributions. Time-frequency transformations include short-time Fourier transform and wavelet analysis, simultaneously capturing temporal and frequency information to reflect dynamic characteristics of non-stationary signals. Complex network analysis, such as scale-free and small-world analyses based on multi-electrode data, reveals overall topological properties of brain networks. Functional connectivity analysis includes coherence and synchrony analyses, evaluating inter-regional functional connections from linear and nonlinear perspectives. Effective connectivity analysis, such as dynamic causal modeling and transfer entropy, further explores causal relationships and information flow between brain regions. Microstate analysis in spatial analysis captures rapidly changing brain network dynamics through whole-brain electrodes. Source localization identifies cortical origins of brain activity, reconstructing spatiotemporal processes of neural activity. Beyond these traditional methods, emerging techniques include nonlinear neurodynamics, complex network analysis, and aperiodic power spectrum analysis. Nonlinear neurodynamics captures EEG's nonlinear features through entropy and information metrics. Complex network analysis treats the brain as a complex system, using graph theory to understand system-level brain characteristics (Li et al., 2020). Aperiodic power spectrum analysis focuses on aperiodic components, extracting their exponents and offsets to reflect the balance between neural excitation and inhibition, enabling differentiation of brain states and neurological disorders (胡静怡等, 印刷中).

Evidently, resting-state EEG analysis is gradually shifting from focusing on rhythmic, linear, and local activities toward aperiodic, nonlinear, and network-based approaches. We summarize major resting-state EEG analysis methods in Table 2 .

Table 2 Major analysis methods for resting-state EEG

Method	Description
Time-domain analysis	Directly extracts relevant waveform features from the time domain
Power spectrum analysis	Converts amplitude-time signals into EEG power-frequency spectra to obtain rhythm distributions and changes
Aperiodic power spectrum	Extracts and analyzes aperiodic components reflecting non-stationary signal characteristics and complexity
Time-frequency analysis	Transforms signals to time-frequency domain to simultaneously capture temporal and frequency information

Method	Description
Wavelet analysis	Decomposes signals into wavelet basis functions at different time scales and frequencies
Microstate analysis	Identifies discrete, brief, and relatively stable brain functional states through scalp potential field configurations
Source localization	Identifies brain regions generating electrical activity from scalp-recorded EEG signals
Coherence analysis	Evaluates linear correlation between two signals at specific frequencies
Synchrony analysis	Assesses functional connectivity through phase-locking value, phase lag index, and phase consistency
Dynamic causal modeling	Evaluates effective connectivity describing dynamic interactions and causal relationships between brain regions
Transfer entropy	Assesses predictive capability between signals, revealing information flow
Scale-free analysis	Evaluates whether brain networks exhibit scale-free network properties
Small-world analysis	Graph-theoretic method assessing brain network topology, balancing local and remote connections

Existing toolkits already incorporate functions for data preprocessing, spectral analysis, source localization, and microstate analysis, with most providing user-friendly interfaces (see Table 3). The EEGLAB toolkit processes continuous and event-related electrophysiological data, offering an intuitive user interface and structured programming environment. Brainstorm provides a clean, simple interface, though advanced analyses require function calls. FieldTrip offers preprocessing and various advanced analysis methods but requires programming expertise. MNE-Python, a subproject of MNE, excels in visualization output. LORETA and its derivatives (sLORETA/eLORETA) perform source analysis of EEG signals to calculate functional connectivity in source space. EMEGS can be used for data preprocessing, analysis, and visualization. SPM can process multiple neuroimaging modalities including fMRI. MICROSTATELAB is an EEGLAB-based toolkit for standardized identification, visualization, and quantification of EEG microstates. FOOOF is a Python toolkit for quantifying 1/f spectral features, extracting periodic and aperiodic components. Most of these software packages are developed based on MATLAB and Python, providing basic to advanced functions for users with different language preferences and programming skills. As analysis techniques advance, more user-friendly and convenient toolkits are expected to emerge.

Table 3 Commonly used software for resting-state EEG analysis

Software	Reference	Primary Functions	Language
EEGLAB	Delorme & Makeig, 2004	Preprocessing, spectral analysis	MATLAB
BrainStorm	Tadel et al., 2019	Preprocessing, source localization	MATLAB
Fieldtrip	Oostenveld et al., 2011	Advanced analysis methods	MATLAB
SPM	Ashburner, 2012	Multimodal neuroimaging data	MATLAB
MICROSTATELAB	Nagabhushan Kalburgi et al., 2024	Microstate analysis	MATLAB
EMEGS	Peyk et al., 2011	Preprocessing, source localization, visualization	MATLAB
DISCOVER-EEG	Gil Ávila et al., 2023	Automated preprocessing	Python
MNE-Python	Gramfort et al., 2013	Visualization, analysis	Python
FOOOF	Donoghue et al., 2020	Aperiodic power spectrum analysis	Python
LORETA	Pascual-Marqui et al., 2002	Source localization	MATLAB

5.2 Artificial Intelligence

Artificial intelligence (AI) has been widely applied in resting-state EEG data analysis. AI standardizes EEG processing, reduces subjective decision-making by human evaluators, provides more objective and transparent methods, and has demonstrated reliability (Hatz et al., 2015). Researchers have also developed computer-aided scoring tools for resting-state EEG that can process large datasets more efficiently (Fraschini et al., 2022).

Currently, AI is extensively used in mental illness diagnosis. Tzimourta et al. (2021) reviewed applications from 2009 to 2021, with most studies using Support Vector Machine (SVM) to diagnose Alzheimer's disease based on α/ ratio 等指标. Resting-state EEG oscillations can be modeled via Random Forest (RF) regression as transdiagnostic predictors of cognitive function, with specific frequency band oscillations successfully predicting cognitive test performance across diagnostic categories without significant differences (Sargent et al., 2021). Some researchers have used resting-state EEG data with supplementary information, employing SVM, RF, and Elastic Net (EN) to build classification models for multiple mental disorders based on Power Spectral Density (PSD) and Functional Connectivity (FC) features, achieving 74.52% to 93.83% accuracy for predicting schizophrenia, trauma-related disorders, anxiety disorders, and other conditions (Park et al., 2021).

Although machine learning has achieved considerable success in cognitive assessment and mental illness diagnosis, EEG signals contain multi-level features including spectral, connectivity, and microstate characteristics that easily form high-dimensional feature sets. Traditional machine learning methods rely on manual feature engineering, struggle to effectively represent high-order nonlinear features in neurophysiological data, and are susceptible to the curse of dimensionality. In contrast, deep learning effectively addresses these limitations through automatic feature extraction, modeling temporal dependencies, and enhanced robustness to signal variability, automatically learning complex diagnostic patterns for large-scale applications. Researchers have successfully identified EEG features related to specific cognitive states and behavioral patterns using Deep Convolutional Neural Network (DCNN) models (Gemein et al., 2024). Deep convolutional neural networks also show outstanding performance in sex prediction, achieving 84.1% balanced accuracy (Khayretdinova et al., 2024). Deep learning is also used to predict brain age, offering new perspectives for understanding cognitive development and aging (Gemein et al., 2024). Particularly in clinical applications, deep learning enables precise diagnosis and robust neuropsychiatric disease diagnostic models. Lin et al. (2024) compared traditional machine learning with deep learning methods for feature extraction and depression diagnosis, finding that deep learning automatically learns complex feature representations and offers advantages when processing large-scale datasets. Specifically, for depression diagnosis models, Khan et al. (2024) achieved 100% accuracy with a 2D-CNN model; Duan et al. (2020) developed DeprNet combining CNN and LSTM with 99.37% accuracy; Wan et al. (2020) reported 99.12% accuracy with HybridEEGNet; and Xu et al. (2023) achieved 99.9% accuracy with a CNN-LSTM model. Researchers have also developed Parkinson's disease (PD) classification models using deep learning, achieving 99.2% accuracy, 98.9% precision, and 99.4% recall when classifying PD patients and healthy controls. Moreover, the model shows sensitivity to dopaminergic medication effects, providing powerful tools for PD 辅助诊断 and monitoring (Lee et al., 2021).

However, current resting-state EEG research faces two major challenges: lack of large-scale datasets for robust feature extraction and evaluation, and general models limited by electrode configurations, data formats, and sampling rates that can only be trained on single datasets. Consequently, researchers have proposed several EEG foundation models.

EEG foundation models demonstrate excellent performance, significantly improving classification accuracy. BrainWave is an EEG foundation model based on 40,000 hours of data from 16,000 participants, capable of extracting highly discriminative features from complex EEG data with domain transfer capabilities. In seizure detection tasks, BrainWave achieved a mean area under the curve of 91.93%, significantly outperforming other models (Yuan et al., 2024).

EEGPT employs autoregressive pretraining with electrode modeling strategies, integrating data from 138 electrodes and accumulating 37.5 million pretraining samples to precisely capture temporal dependencies in EEG data. EEGPT improved average accuracy by 5.07% in emotion recognition tasks and 11.20% in sleep stage classification tasks compared to traditional models (Yue et al., 2024). LEAD is the first foundation model for Alzheimer's disease EEG detection, demonstrating excellent performance in sample-level and subject-level classification tasks, with maximum score improvements of 9.86% over existing methods. LEAD effectively extracts disease-critical EEG features through sample-level and subject-level contrastive learning while minimizing inter-individual variability interference (Wang et al., 2025).

Notably, resting-state EEG features simple acquisition without external stimulation, broad subject applicability, and multi-scenario adaptability. Combined with wearable devices, it has strong potential for creating large-scale datasets with tens of thousands of participants. EEG foundation models offer new solutions for resting-state EEG data expansion. FEMBA employs bidirectional state space modeling, dramatically improving efficiency and reducing computational costs for large-scale EEG data processing compared to traditional Transformer architectures. The model provides variants of different sizes, with the tiny model (7.8M parameters) performing excellently on resource-constrained devices, enabling real-time EEG monitoring on wearables (Tegon et al., 2025). AI can also generate resting-state EEG data. Pan et al. (2024) used deep learning to generate synthetic EEG data with frequency characteristics highly consistent with real data, improving classification accuracy by up to 35.67% when used for training. Carrle et al. (2023) employed Conditional Wasserstein Generative Adversarial Network (cWGAN) based on public datasets to generate data highly similar to real data in time and frequency domains, improving major depressive disorder diagnosis accuracy by nearly 10%. Farahzadi et al. (2025) generated EEG signals based on the Leipzig Mind-Brain-Body Database with almost no difference in statistical and spectral feature consistency compared to real data.

With rapid AI development, AI applications in resting-state EEG will continue expanding. Combined with large-sample databases, future researchers will identify more EEG markers for neuropsychiatric disorders, further improving diagnostic accuracy, promoting personalized medicine, simplifying diagnostic procedures, improving patient outcomes, and establishing precise disease diagnostic models (Kurbatskaya et al., 2023). AI, particularly EEG foundation models, is expected to expand existing resting-state EEG data, breaking limitations of subject populations and brain states, and addressing data scarcity in specific clinical scenarios. Resting-state EEG has become a pioneering demonstration field for electrophysiology combined with AI.

6.1 FAIR Principles for Data Sharing

International data contribution FAIR principles (Findable, Accessible, Interoperable, and Reusable) provide a clear framework for data sharing, aiming to improve data transparency and equity to ensure efficient sharing and utilization among researchers (Wilkinson et al., 2016). However, EEG data sharing still faces numerous challenges. Different laboratories use various acquisition equipment and data formats, limiting data accessibility and operability.

Shared data storage and circulation require universal EEG data sharing formats. The Brain Imaging Data Structure (BIDS) for EEG is an internationally recognized standard defining directory structures, file naming conventions, and metadata formats (Gorgolewski et al., 2016). This standard is commonly used across multiple data sharing platforms including OpenNeuro. The EEG-BIDS specification organizes data by subject, with each subject's directory containing subdirectories for multiple experiments and data modalities, accompanied by dataset documentation. Various toolkits and software can convert raw EEG data to BIDS format: (1) BIDS converters included in EEG analysis packages; (2) General-purpose tools for data querying and operations such as PyBIDS and BIDS-MATLAB; (3) BIDS analysis tools like BIDS Apps. Common EEG storage formats include EDF, GDF, etc. Format conversion often requires external tools, creating obstacles for dataset sharing and circulation. The EDF format and its extended version EDF+ are the most common storage formats for electrophysiological signals, simple and versatile, supporting multiple physiological signal types. The header records basic information including sampling rate, channel count, and signal type, while the data section stores specific signal values by channel. Currently, EEG-BIDS also recommends EDF as its preferred format.

Implementation of FAIR principles, particularly EEG-BIDS promotion, is expected to further advance resting-state EEG data sharing.

6.2 Development of Resting-State EEG Research in China

Currently, China has relatively few shared datasets, with publicly available datasets including resting-state EEG data for sleep deprivation (Xiang et al., 2024) and multimodal open datasets for mental disorder analysis (Cai et al., 2022). Domestic brain research tends to favor sharing resting-state fMRI data, while EEG data sharing remains limited due to easy accessibility and severe noise issues. On the other hand, China has launched multiple large-scale EEG and brain-computer interface projects that will greatly enrich domestic EEG data collection and sharing. For example, the China Brain Project aims to establish a multi-dimensional database of Chinese brain health to support precise diagnosis and intervention for major brain diseases (陆林等, 2022). In analysis software, domestic scholars developed the Reference Electrode Standardization Technique (REST), which converts multi-channel EEG recordings to approximate zero reference, reducing potential biases from other references (Dong et al., 2017).

To enhance China's international influence in resting-state EEG research, we should vigorously promote open science culture and facilitate international cooperation. We believe future domestic EEG data sharing and analysis software development will achieve more results, contributing Chinese wisdom to global brain science research.

6.3 Significance for Brain Health

Future research should expand resting-state EEG applications through large-scale cohort studies. Resting-state EEG is easy to acquire, adaptable to broad populations, and suitable for establishing large-scale databases. However, scarcity of high-density, high-sampling-rate datasets limits its promotion. We recommend researchers systematically build resting-state EEG databases, focusing on: (1) expanding database scale and quality; (2) covering broader neuropsychiatric populations in clinical fields, such as epilepsy, schizophrenia, and autism; (3) emphasizing database construction for infants, children, adolescents, and elderly to achieve lifespan coverage. Additionally, longitudinal cohort designs help track brain activity pattern changes with age, crucial for understanding neurodegenerative diseases and cognitive aging.

Technological advances will be central to resting-state EEG development. First, electrode types will become more diverse, with flexible and dry electrodes enabling long-term recordings. Second, advances in image recognition will facilitate more convenient and efficient electrode localization. Finally, AI integration will provide new perspectives for resting-state EEG data analysis, with machine learning and deep learning dramatically improving processing efficiency and accuracy, even substantially expanding existing datasets at the technical level. We expect AI to reveal more precise EEG biomarkers, providing objective indicators for early intervention and personalized treatment.

Combining large-sample cohort studies, sensor technology, and AI, future research may construct more accurate brain functional network models, offering new insights into neuropsychiatric disease pathophysiology. This will not only advance basic neuroscience but also revolutionize clinical practice, particularly in disease prevention, early diagnosis, and treatment strategy development. Open-access high-density resting-state EEG will undoubtedly provide scientific foundations and technical support for brain health worldwide.

Conclusion

Open-access high-density resting-state EEG data is crucial for advancing cognitive neuroscience. Through compilation and analysis of existing public databases, we see that resting-state EEG is essential for revealing intrinsic brain activity patterns, understanding biomarkers for neuropsychiatric disorders, and exploring neural foundations of human cognition and behavior. However, currently available datasets remain unbalanced in geographic distribution, subject populations, and application fields. Future efforts should build more standardized and diverse databases and develop advanced processing tools to promote effective utilization of high-density resting-state EEG data. With technological progress and maturation of data-sharing culture, we believe high-density resting-state EEG will provide powerful data support for unraveling the mysteries of the human brain.

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