Foundation and Large-Scale AI Models in Neuroscience: A Comprehensive Review

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Abstract

The advent of large-scale artificial intelligence (AI) models has a transformative effect on neuroscience research, which represents a paradigm shift from the traditional computational methods through the facilitation of end-to-end learning from raw brain signals and neural data. In this paper, we explore the transformative effects of large-scale AI models on five major neuroscience domains: neuroimaging and data processing, brain-computer interfaces and neural decoding, molecular neuroscience and genomic modeling, clinical assistance and translational frameworks, and disease-specific applications across neurological and psychiatric disorders. These models are demonstrated to address major computational neuroscience challenges, including multimodal neural data integration, spatiotemporal pattern interpretation, and the derivation of translational frameworks for clinical deployment. Moreover, the interaction between neuroscience and AI has become increasingly reciprocal, as biologically informed architectural constraints are now incorporated to develop more interpretable and computationally efficient models. This review highlights both the notable promise of such technologies and key implementation considerations, with particular emphasis on rigorous evaluation frameworks, effective domain knowledge integration, and comprehensive ethical guidelines for clinical use. Finally, a systematic listing of critical neuroscience datasets used to derive and validate large-scale AI models across diverse research applications is provided.

Keywords: Foundation model, brain imaging, computational neuroscience, brain disorders, artificial intelligence.

1 Introduction

The rise of large-scale artificial intelligence (AI) models, including foundation models (FMs) and large language models (LLMs), has opened a new era at the intersection of AI and neuroscience. These models are excellent at learning multimodal, rich representations from large, varied datasets [1, 2, 3]. Compared to classical computational approaches that mainly relied on conventional machine learning methodologies like support vector machines, linear discriminant analysis, and ensemble methods with manually engineered features [4], this paradigm shift represents a significant departure. For example, FMs exhibit strong generalization across a variety of experimental conditions, subjects, and recording modalities, and they can capture the intricate spatiotemporal dependencies found in neural signals [5]. This is achieved through end-to-end learning of hierarchical representations directly from raw brain signals [6]. In this context, neural signals refer broadly to electrophysiological and neuroimaging recordings, such as EEG, MEG, sEEG, ECoG, CT, fMRI, etc., which capture brain activity across different spatial and temporal scales. These diverse modalities provide complementary perspectives on neural dynamics, offering rich data for large-scale representation learning.

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Despite these capabilities, data scarcity constrains their full potential in neuroscience applications. Self-supervised learning (SSL) approaches have addressed a major bottleneck in neuroscience: the limited availability of large-scale labeled neural datasets [7]. Brain foundation models (BFMs) specifically designed for neural signal processing have achieved unprecedented success by leveraging contrastive learning frameworks and transformer architectures. These models perform well in predicting neuronal responses to novel stimuli, generalizing across subjects with minimal fine-tuning, and uncovering fundamental principles of neural computation that were previously inaccessible. [8, 9, 10]. For instance, BErt-inspired Neural Data Representations (BENDR), adopted SSL by integrating transformer architectures with contrastive learning objectives to produce robust EEG representations [9]. These achievements have facilitated the development of models that can decode intended speech from neural signals at near-conversational speeds, predict seizure onset with remarkable accuracy, and detect biomarkers for neurodegenerative diseases years before clinical symptoms emerge. [11, 12]. Building on these foundational advances, the integration of large-scale multimodal models has driven great advances in cross-modal neural decoding applications and related clinical translation. Vision-language models such as Contrastive Language–Image Pre-training (CLIP) generate informative latent representations that capture cross-modal semantic relationships, enabling the alignment of neural activity patterns with textual descriptions or visual stimuli [13]. In clinical settings, clinical decision support systems powered by FMs now integrate multimodal patient data—including neuroimaging, genetic data, clinical histories, and real-time physiological monitoring—to provide evidence-based recommendations for treatment optimization [14, 15]. Furthermore, generative AI models with latent diffusion architecture demonstrated extraordinary capabilities of reconstructing visual experiences from brain activity while fMRI signals turned out to be effective cues for producing high-fidelity natural scene reconstructions [16]. Analogously, recent breakthroughs of neural data augmentation rely on diffusion models to produce synthetic EEG signals and thus improve model robustness in situations with restricted availability of data [17]. Recent works increasingly combine heterogeneous neuroimaging modalities, genomic information, clinical metadata, and external variables to build complete models of brain function and pathology [18, 19]. These advancements created a mutual interdependence of neuroscience and AI research. Moreover, brain-inspired architecture with biological constraints and neural codes improved model interpretability, robustness, and computational efficiency [20, 21]. Meanwhile, recent findings indicate that LLMs are able to predict neuroscience experiment results with a success rate of more than 80%, process scientific literature, and produce original hypotheses and aid experiment design [22]. These results have generated practical neuromorphic processors like Intel's Loihi and IBM's TrueNorth and implemented brain-inspired AI computing paradigm for energy-efficient AI computing [23, 24]. Studies of spiking neural networks, neuromorphic computing, and biologically possible attention mechanisms continue both the extension of our knowledge of biological intelligence and more advanced AI systems [24, 25, 26]. Evolution from classical ML towards current multimodal and generative models has dramatically improved the ability of neural activity decoding, brain function interpretation, and AI system development aiming at emulating biological computation. [27, 28, 29, 30].

We refer throughout this article broadly to FMs as "large-scale AI models" and refer as an example to LLMs, vision-language models, and other transformer-based and generative models trained with millions or billions of parameters. Our review reveals five overarching domains of applications that together demonstrate the paradigm-shifting effects of applying large-scale AI models to neuroscience research. First, we cover neuroimaging and data processing applications involving specialty neuroimaging models of brain structure analysis, neural signal process models of interpretation of electrophysiological data, and multimodal integration methods combining heterogeneous imaging modalities. Then we report brain-computer interfaces and neural decoding systems employing large-scale models and achieving record-level performance, translating neural activity into useful outputs. Thirdly, we explore molecular neuroscience and genomic modeling, involving both genomic FMs for variant interpretation and data-driven approaches for genetic risk prediction and disease mechanism discovery. Subsequently, we review clinical support and translational frameworks involving both clinical decision support systems and knowledge-driven AI methods of cognitive modeling and diagnostic support. Finally, we review applications targeting neurological and psychiatric disorders, spanning neurodegenerative conditions, acute neurological injuries, structural brain abnormalities, major psychiatric illnesses, trauma-related pathology, and neurodevelopmental disorders.

Our survey unveils that extensive-scale AI models are revolutionizing neuroscience through their capacity to provide robust generalization from heterogeneous neural datasets and experiment condi-

tions, and tackle core issues such as multimodal data fusion, spatiotemporal pattern explanation, and translation of research outputs into clinical applications. These reviewed applications span both foundational research aims, e.g., neural coding principles and brain network dynamics understanding, and translational aims that target enhanced diagnostic accuracy and therapy efficacy, spanning a variety of neurological as well as psychiatric disorders. Moreover, this article chronicles contemporary accomplishments as much as elucidates vital future research directions and key challenges fundamental to furthering the subject.
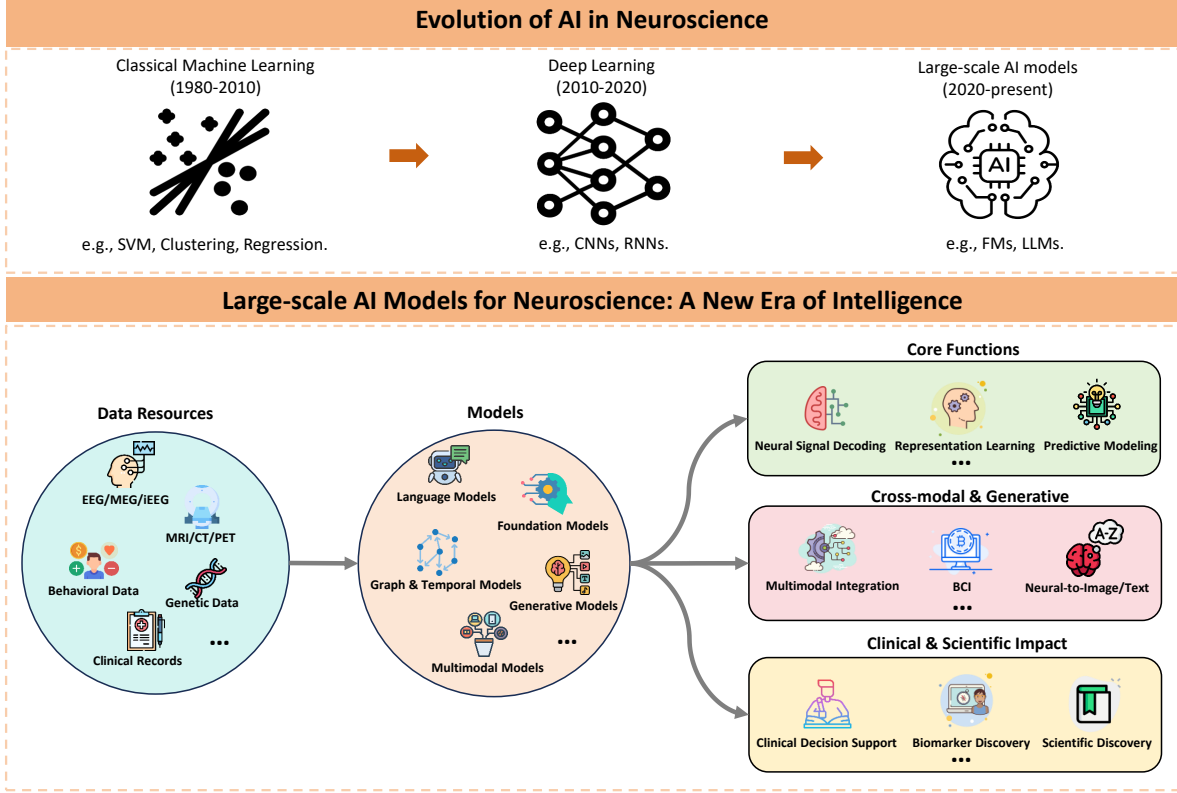

Figure 1: Neuroscience AI Landscape: Developmental Trajectory and Functional Framework.

2 Background and Problem Formulation

2.1 Theoretical Foundations of Large-scale AI Models

2.1.1 From Classical Machine Learning to FMs

The development of AI in neuroscience has witnessed a shift from task-specific machine learning techniques to cohesive, generalizable FMs. In the initial phase, conventional machine learning techniques, such as support vector machines, linear discriminant analysis, and ensemble methods, were overly dependent on manually crafted features extracted from neurophysiological measures [4]. Although such techniques were able to produce decent performance in particular domains, their low generalization capability and requirement of domain expertise during feature engineering restricted their wide usage. Deep learning systems radically altered this paradigm through the capability of end-to-end learning of hierarchical representations from raw neural recordings [6]. Nevertheless, deep learning systems are often determined by extensive annotated data and are still task-specific, posing limitations on their transferability and generalizability across various neuroscience applications and experimental settings. With increasing access to large-scale data and computational capabilities, FMs have lately risen and established unprecedented capabilities with a description of their capacity to grow through a plethora of tasks, domains, and modalities with a common set of architectural frameworks [1]. These models tap into extensive datasets and auto-supervised learning frameworks and gain general-purpose knowledge,

enabling each of them to adapt and perform a variety of neuroscience tasks with small extra data usage during fine-tuning. The panorama of neuroscience AI models from fundamental computational functions through cross-modal capabilities and clinical repercussions is contextualized in Fig. 1.

2.1.2 Scaling Laws and Core Principles

As opposed to classical models, high-scale AI systems are constructed from the transformer architecture that proposes self-attention as a fundamental mechanism of dealing with intricate dependencies of data [31]. Self-attention mechanism allows models to detect and combine pertinent contextual information from time and space, a feature that comes especially useful while dealing with neural signals with high temporal dynamics and spatial organization. These models are subject to empirical scaling laws that govern their performance features and exhibit consistent gains when the model size, training data, and computational capacity are each incremented proportionally [32]. For neuroscience applications, the resulting scaling behavior means that with larger model size and longer neural training datasets, better performance can be achieved in neural decoding tasks involving signal reconstruction and cross-subject generalizability. Scaling-enabled emergent capabilities are a few-shot learning that allows models with little additional training data to generalize and adapt to a new task and transfer learning with changing neural recording modalities and experiment conditions.

2.2 Architectural Frameworks and Design Principles

2.2.1 Transformer Architecture in Neuroscience Applications

The transformer architecture has become the foundational design of most large-scale AI models in neuroscience, due to its capacity to efficiently capture long-range dependencies in both spatial and temporal dimensions [31]. This flexibility can extend easily to multimodal brain data, enabling the fusion of EEG signals, MRI volumes, and neuro-symbolic representations in neuroscience contexts. The details are listed in Table 1.

For brain signal modeling, transformers have been successfully adapted to EEG and MEG domains. For instance, Brain Neural Transformer (BRANT) is a representative FM that applies multi-layer transformers to intracranial EEG data for generalized neural decoding across patients and tasks, with attention modules capturing both short- and long-range neural dependencies [8]. Similarly, CBraMod employs cross-attention transformer structures to decode EEG into cognitive states, enhancing accuracy in low-data regimes [33].

Table 1: Transformer Architecture Applications Across Neuroscience Domains

Domain	Key Challenges	Transformer Advantages	Model Examples
EEG/MEG Analysis	Non-stationarity, temporal dynamics, artifacts	Long-range temporal modeling, self-attention for time-series	BRANT [8], CBraMod [33], BENDR [9]
MRI Decoding	High dimensionality, inter-subject variability	Spatiotemporal attention, contextual encoding	MindBridge [15], MindEye2 [34]
Structural MRI	Anatomical variability, low contrast structures	Patch tokenization, cross-slice attention	BrainSegFounder [35], AnatCL [36]
Multimodal Neuroimaging	Cross-modal alignment, data heterogeneity	Cross-modal attention, joint representation learning	BrainCLIP [37], MultiViT [38]
Clinical NLP	Medical terminology, reasoning, sparse context	Pretrained LLMs, in-context learning, entity linking	NeuroGPT [39], AtlasGPT [40]
Genomics	Predicting function of genetic variants	Capturing long-range genomic interactions	AlphaGenome [41], Enformer [42]
Seizure Video Analysis	Variable semiology, temporal dynamics, environmental variability	Long-range temporal modelling, robust feature representation, multimodal integration	SETR-PKD [43], VSViG [44]

In addition to brain signal analysis, transformers play an important role in other complex tasks, including segmentation and reconstruction. Models such as MindEye2 process shared-subject fMRI data through transformer layers that align voxel patterns with latent visual embeddings, enabling image reconstruction with minimal training data [34], where the attention mechanism demonstrates great capability in handling brain shape variability and imaging resolution differences across subjects and institutions.

2.2.2 Multimodal Integration Architectures

The ability to integrate multiple data modalities has become increasingly critical in neuroscience applications, enabling joint processing of heterogeneous neural data types to achieve a deeper understanding

than traditional single-modality approaches [13]. These architectures leverage complementary information across different data types, including imaging data, temporal signal recordings, genetic data, and behavioral measurements.

Table 2: Multimodal Fusion Strategies in Neuroscience FMs

Fusion Level	Fusion Mechanism	Model Examples	Fusion Objectives
Early Fusion	Token-level or embedding concatenation; joint encoder input	BENDR [9], Wei et al. [45]	Cross-modal representation learning; Sleep staging
Mid Fusion	Shared attention layers; cross-token interactions across modalities	BrainCLIP [37], MindBridge [15]	Multimodal decoding; visual reconstruction
Late Fusion	Separate encoders with decision-level combination (e.g., ensemble or MLP)	SHADE-AD [46], HybridTransNet [47]	Alzheimer's diagnosis; Tumor segmentation
Prompt-based Fusion	Text prompts guiding cross-modal attention or LLM generation	DECT [48], Mental-LLM [49]	Clinical reasoning; psychiatric assessment
Contrastive Alignment	Cross-modal contrastive learning with shared embedding space	NeSyGPT [50], BrainCLIP [37]	Semantic alignment; zero-shot generalization
Hierarchical Fusion	Multi-stage modality integration (e.g., audio→video→text)	VS-LLM [51], Centaur [52]	Human behavior prediction; multimodal psychiatric diagnosis

The key principle of multimodal neural architectures lies in learning joint representations that bridge different data modalities while preserving modality-specific information. To achieve this goal, contemporary approaches typically employ encoder-decoder frameworks where separate encoders process each modality before aggregating representations of different modalities in the fusion stage. Recent developments have demonstrated remarkable progress in cross-modal reconstruction tasks, particularly in translating fMRI signals to natural scene imagery using generative latent diffusion models [16] and conditional diffusion models for vision decoding [53]. The details are shown in Table 2.

While these achievements demonstrate the potential of multimodal approaches, several technical challenges remain in developing robust neural signal integration frameworks. A primary challenge lies in temporal alignment across heterogeneous neural signals, as modalities such as fMRI, EEG, and MEG exhibit fundamentally different temporal resolutions. To address this challenge, researchers have developed hierarchical attention mechanisms and multi-scale temporal modeling approaches that can synchronize these different data streams while maintaining the detailed timing information crucial for accurate analysis [10]. Another advanced model, MindBridge, has demonstrated significant improvements in reconstruction fidelity and generalization capabilities by employing sophisticated fusion mechanisms that can effectively generalize across diverse individuals and recording sessions [15].

2.3 Training Methodologies and Learning Paradigms

Table 3: Self-Supervised Learning Methods for Neural Representation Learning

SSL Method	Description	Model Examples	Key Benefits
Masked Signal Modeling	Predict missing segments of neural recordings using surrounding context	BENDR [9], EEGFormer [54]	Context-aware embeddings, Long-range dependency modeling
Contrastive Learning	Maximize agreement between semantically similar neural signals or modalities	BrainCLIP [37], AnatCL [36]	Modality alignment, Invariant features
Masked Patch Prediction	Reconstruct missing image patches from spatial brain volumes	BrainSegFounder [35], FM-CT [55]	Spatial representation, Anatomical priors
Temporal Forecasting	Predict future neural signals from past time steps	BRANT [8], BrainLM [56]	Predictive dynamics, Temporal generalization
Cross-modal Alignment	Learn shared embeddings across different input modalities	MindBridge [15], BrainCLIP [37]	Modality fusion, Semantic grounding
Sequential Modeling	Capture patterns in sequential neural data	CBraMod [33], EEGFormer [54]	Time-series modeling, Sequential decoding

Self-supervised learning has become a key training approach for large-scale neuroscience AI models, overcoming the scarcity of labeled neural data by learning meaningful representations directly from neural activity patterns [57]. Unlike supervised learning approaches, SSL eliminates the reliance on manual data labeling by creating learning tasks directly from the neural data, making it ideal for scalable pretraining in neuroscience where labeled datasets are scarce.

As illustrated in Table. 3, various self-supervised objectives have been successfully adapted to the neuroscience domain, with reconstruction-based and contrastive methods representing two major paradigms. Reconstruction-based approaches, particularly masked signal modeling. Reconstruction-based approaches, particularly masked signal modeling, involve randomly masking portions of neural signals and training models to reconstruct missing segments based on surrounding context, encouraging learning of robust representations that capture both local temporal patterns and long-range dependencies. For example, BENDR uses contrastive loss functions to distinguish temporally adjacent and distant EEG segments, learning context-aware representations of neural time series data [9].

EEGFormer incorporates masked sequence modeling and attention mechanisms for pretraining on large-scale EEG datasets [54].

In contrast, contrastive learning focuses on learning invariant representations across different experimental conditions, subjects, and recording sessions. In brain imaging tasks, models like Brain-SegFounder adopt two-stage pretraining pipelines combining vision transformers with self-supervised objectives such as patch prediction for reconstructing masked brain image regions [35]. These approaches enable models to capture detailed spatial and anatomical patterns critical for segmentation and analysis tasks.

2.3.1   Training Pipeline

Self-supervised methods require specially crafted training pipelines to unlock their full capabilities. Large models are part of a systematic multi-step process. As depicted in Fig. 2, there are three high-level steps. These are pre-training as a pre-requisite of universal knowledge acquisition, adaptation as a step of task-specific tuning, and inference and deployment as a step of real-world use [1].

Pre-training Stage: Pre-training constructs general knowledge from large-scale datasets. Self-supervised learning methods are applied at this stage by models. FMs are trained from diverse sources of data, including text corpora, image-text pairs, audio streams, and biological signals [1, 13]. It is crucial to have diverse data, as this enables models to discover universal patterns that perform well across different tasks and domains [58].

Adaptation Stage: The adaptation phase adapts pre-trained models to specific tasks. It utilizes restricted labeled data from target domains at this phase. Adapting is crucial for neuroscience applications because datasets in this area generally contain little labeled data [59]. Also, complete model redeployment produces computational bottlenecks. Parameter-efficient tuning techniques resolve this issue and are comprised of adapter tuning, prompt tuning, and Low-Rank Adaptation (LoRA). These techniques are efficient yet require less computational effort [60, 61, 62].

Inference and Deployment Stage: The deployment stage centers around real-world implementation. Inference should be efficient in systems during real-world use. Safety ensures correct use. Interpretability and ethics also guide. Deployment abilities are improved with advanced methods. Retrieval-Augmented Generation (RAG) incorporates external databases of knowledge. Methods of knowledge-grounding make predictions consistent with domain knowledge [63]. Moreover, applications in neuroscience require systems with multimodal decoding capabilities to analyze and integrate diverse signal types for comprehensive analysis.

2.4   Challenges and Considerations for Neuroscience Applications

2.4.1   Domain-Specific Challenges

Applying large-scale AI models to neuroscience involves unique challenges. These challenges stem from the distinctive nature of neural data. Neural signals exhibit distinct properties that differentiate them from natural language or computer vision domains. These properties include high temporal resolution, multi-channel spatial organization, non-stationary dynamics, and substantial inter-subject variability [64, 65].

Cross-subject and Cross-session Generalization: One of the most significant challenges involves substantial variability in neural signals. This variability occurs across different subjects and recording sessions. Inter-subject variability arises from several sources. These include anatomical differences, cognitive strategies, and individual neural characteristics. Inter-session variability results from different factors. These factors include electrode placement variations and recording equipment differences [66]. Researchers can formulate this challenge as a domain adaptation problem. Models must learn representations that remain robust to irrelevant variations. At the same time, these models must preserve task-relevant information.

Temporal Dynamics and Multi-scale Dependencies: Neural signals exhibit complex temporal dynamics that span multiple timescales. They range from millisecond-level action potentials to minute-level cognitive states. Capturing these multi-scale temporal dependencies presents a significant methodological challenge. This challenge requires maintaining computational efficiency. Efficient attention mechanisms and hierarchical modeling approaches are necessary to address this issue [67].
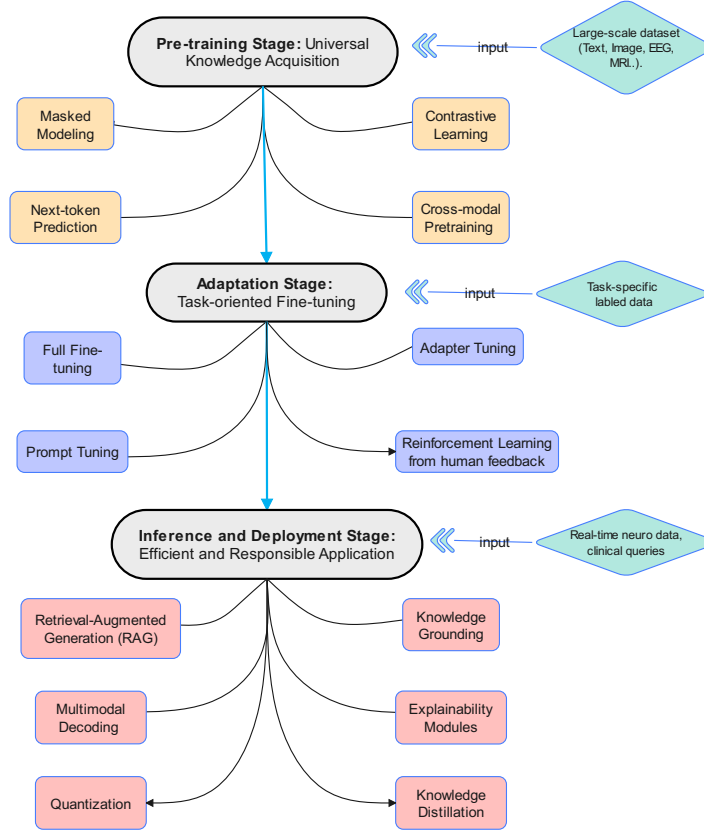
Figure 2: Basic pipeline of Large-Scale AI Models

2.4.2 Tokenization and Neural Signal Representation

The conversion of continuous neural signals into discrete tokens amenable to transformer-based models is a crucial methodological issue particular to neuroscience applications. In contrast with natural language processing, where natural units of meaning are words, neural signals necessitate advanced tokenization techniques that are able to preserve spatiotemporal information and permit efficient processing. For EEG and MEG recordings, tokenization generally entails segmenting continuous recordings into fixed-duration time windows such that each window corresponds to a discrete token. Optimizing the duration of this window involves balancing the resulting spatiotemporal resolution with computational requirements. Multichannel recordings necessitate consideration of inter-electrode spatial relations as well; often through channel-wise processing with subsequent use of a spatial attention mechanism or graph neural network module modeling the inter-electrode connectivity patterns [68]. For fMRI recordings, the intrinsically lower spatiotemporal resolution with attendant higher spatial detail necessitates alternative tokenization methods. These generally incorporate voxel-wise or region-of-interest-based tokenizations utilizing learned spatial embedding vectors that compact high-dimensional voxel information into compact tokens whilst retaining spatial relations and patterns of functional connectivities [69].

2.4.3 Interpretability and Biological Plausibility

Interpretability of AI models in neuroscience throws up special challenges going well beyond conventional explainable AI methods, requiring models with both predictive performance and biological realism. AI models' learned representations should best align with established functional brain networks, adhere to anatomical constraints of connectivities, and display temporal behavior analogous to neurophysiological mechanisms [70]. It requires the creation of assessment frameworks that evaluate both predictive capacity and biological realism and get the learned representations right and still meet research application utility requirements.
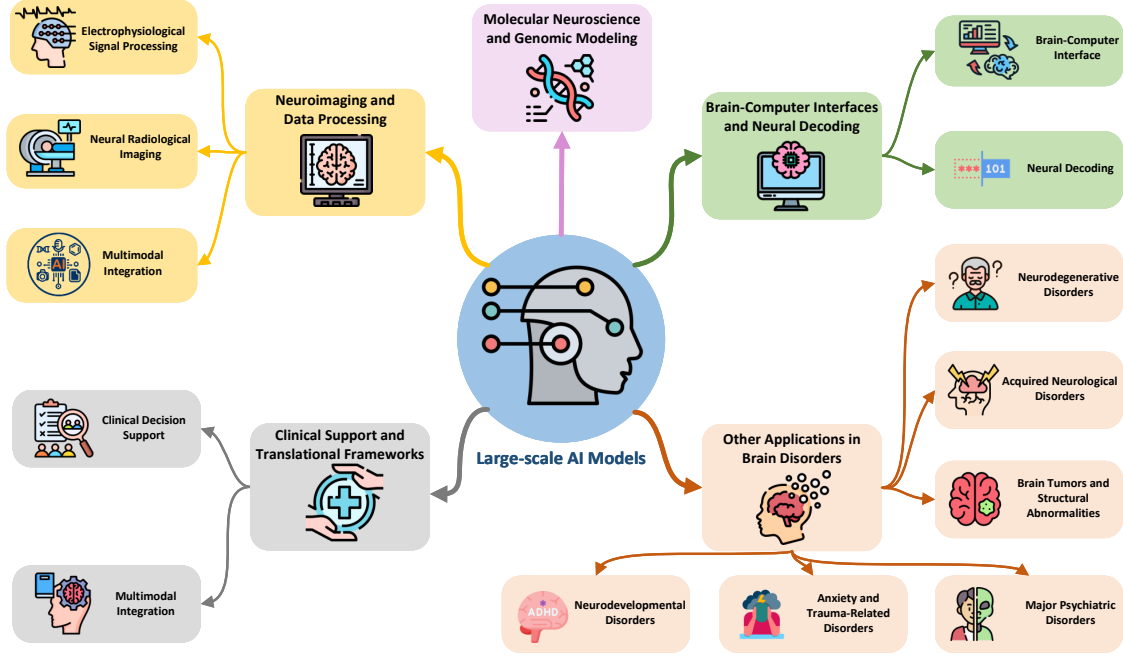
Figure 3: Overview of large-scale AI model applications in neuroscience. Five major application domains are shown, demonstrating the bidirectional relationship between neuroscience and AI development and identifying key research challenges.

2.4.4 Data Quality and Standardization

The effectiveness of large-scale AI models largely depends on the availability of high-quality, standardized datasets that allow extensive training and evaluation. Neural data collection involves a myriad of technical details ranging from recording device specifications to experiment paradigms and preprocessing streams and artifact rejection techniques that are otherwise significant determinants of data quality and inter-study comparison of results [71]. Addressing such variations requires extensive standardization of data that covers technical aspects of sampling rates and filtering criteria, and coordinate systems along with methodological variables of experiment designs and behavioral task specifications. Standardized protocol and data formats permitting scalable training of models with adequate diversity enabling proper generalization are a big challenge. Though the Brain Imaging Data Structure (BIDS) project provides a foundational outline of neuroimaging data organization with a standardized approach, extension of the same ideas with a view of incorporating the complete array of modalities of neural recording remains an ongoing venture [72]. Enunciation of the above challenges and methodological frameworks paradigmatically opens the path of successful use of large-scale AI models across neurosciences domains as a subject of elaboration in the sections that follow.

3 Applications of Neuroscience

Large-scale AI models are applied across several neuroscience areas, as shown in Fig. 3, and can systematically be grouped into neuroimaging and data processing, brain-computer interfaces, genomic modeling, and clinical translation. These applications capitalize on the ability of large-scale AI models to decipher intricate neural patterns and uncover underlying laws of brain organization and function. Each group uses different architectures and methods, ranging from FM pretraining from multimodal neural data to fine-tuning with interpretability frameworks and tackling specific neuroscience research and clinical practice challenges. These methods build computational foundations of understanding neural mechanisms and permit applications in diagnostics, therapeutics, and neurotechnology across laboratory and clinical applications.

3.1 Neuroimaging and Data Processing

Large-scale AI models have revolutionized neuroimaging and data processing to allow sophisticated analysis of brain structural images, functional connectomes, and integration of neural data across modalities. FMs dedicated to specific neuroimaging modalities, such as structural and functional MRI and electrophysiological recordings, correspondingly tackle modality-specific issues of spatial resolution, temporal resolution, and inter-subject variation. These models use self-supervised learning, multimodal fusion, and transfer learning to push neuroimaging beyond classical computational methods.

3.1.1 Neural Radiological Imaging Models

Large-scale AI models for neuroimaging have demonstrated strong performance in brain structure and function analysis across multiple imaging modalities, particularly in segmentation, reconstruction, and cross-subject generalization tasks. These models exploit large datasets and advanced architectures to capture complex spatial and anatomical patterns in brain imaging data.

Functional MRI FMs: FMs for functional MRI analysis have gained prominence through advances in brain-to-image reconstruction and functional connectivity modeling. These approaches utilize large-scale neuroimaging datasets and employ self-supervised strategies adapted from computer vision. Brain Language Model (BrainLM) exemplifies this development by training on UK Biobank and Human Connectome Project data, this model uses masked patch prediction to learn brain activity representations [56]. BrainLM supports pretraining, zero-shot inference, and fine-tuning applications. It can predict psychological measures including neuroticism, PTSD, and anxiety scores from neural signals. This demonstrates the potential for fMRI FMs to connect neuroscience with clinical psychology.

Visual reconstruction from brain activity represents a compelling application of fMRI FMs. These models translate neural patterns into interpretable visual content with remarkable accuracy. The MindEye series pioneered this domain by demonstrating accurate image retrieval from large-scale databases like LAION-5B using only brain activity patterns [73]. MindEye2 advances this work through shared-subject modeling that enables effective reconstruction with minimal training data. This model utilizes the Natural Scenes Dataset to achieve high-fidelity visual reconstructions across 8 subjects [34]. These developments mark significant progress toward practical brain-computer interfaces for visual communication and accessibility applications.

Sophisticated architectural innovations have advanced the quality and controllability of neural-to-visual translation. MinD-Vis introduces frameworks combining Sparse-Coded Masked Brain Modeling with Double-Conditioned Latent Diffusion Models. The approach trains on extensive datasets spanning 136,000 fMRI segments from 340 hours of scanning across HCP, GOD, and BOLD5000 datasets [53]. This method achieves exceptional visual scene reconstruction while maintaining interpretability of neural representations. Dual conditioning mechanisms enable precise control over semantic content and visual details in reconstructed images.

Generative modeling approaches have evolved to incorporate region-specific analysis and semantic understanding of neural representations. Earlier transformer-based architectures, such as the Brain Network Transformer and hierarchical spatio-temporal generative models [74, 75], focused primarily on task-specific fMRI analysis without large-scale or multimodal pretraining. Building upon these foundations, recent works have begun integrating FM and language-based paradigms for cross-modal understanding. Generative modeling approaches have evolved to incorporate region-specific analysis and semantic understanding of neural representations. Brain-Diffuser advances this paradigm through ROI-based analysis integrated with CLIP embeddings. This enables semantically meaningful reconstructions that capture both low-level visual features and high-level conceptual content [16]. Cross-subject generalization capabilities have been enhanced through multi-individual pretraining strategies. NeuroPictor demonstrates this through multi-level modulation that enables robust performance across different subjects and experimental conditions [76]. These advances establish fMRI FMs as powerful tools for understanding the neural basis of visual perception and cognition.

Another significant advancement in neuroimaging FMs has emerged through Brain Graph Foundation Model (BrainGFM), a graph-based approach that models the brain as a complex network of interconnected regions [45]. Unlike previous models using time-series data, BrainGFM introduces a graph-based paradigm leveraging functional and anatomical connectivity patterns through Graph Transformer networks with specialized brain topology encodings. The model is pre-trained on 27 datasets spanning 25 neurological disorders with over 25,000 subjects and 60,000 fMRI scans across 8

brain atlases. This enables atlas-invariant patterns that generalize across parcellation schemes. Key innovations include a unified training framework combining graph contrastive learning and masked autoencoders. The model also incorporates meta-learning optimization for few-shot adaptation and language-guided prompting for zero-shot transfer to unseen conditions. BrainGFM addresses neuroimaging heterogeneity while maintaining computational efficiency.

Structural MRI FMs: FMs for structural neuroimaging are emerging as powerful tools in anatomical analysis and show increasing potential for clinical diagnosis. These models employ specialized architectures designed for 3D volumetric brain data. Robust segmentation capabilities represent a primary focus area. Self-supervised learning strategies have proven effective for handling diverse imaging protocols and anatomical variations across different populations.

Advanced 3D architectures optimized for volumetric brain data processing have established new benchmarks for neuroimaging analysis. BrainSegFounder pioneered this domain through specialized 3D convolutional networks designed for comprehensive neuroimage segmentation. The model achieves robust performance across critical clinical tasks including brain tumor segmentation and lesion detection [35]. Self-supervised pretraining enables effective handling of diverse imaging contrasts and anatomical presentations encountered in clinical practice.

Cross-institutional generalization has become crucial for practical clinical deployment, where imaging protocols and equipment vary significantly across medical centers. Brain Imaging Adaptive Core (BrainIAC) addresses this challenge through self-supervised pretraining followed by fine-tuning on specific downstream neuroimaging tasks including MRI sequence classification, brain age prediction, tumor mutation classification, and survival analysis. The model achieves superior performance while emphasizing anatomical consistency across multiple neuroimaging benchmarks [77]. This approach proves valuable for multi-site clinical studies and real-world medical applications where robust generalization is essential for reliable diagnostic support.

Weakly supervised approaches have demonstrated exceptional capability in capturing subtle anatomical variations associated with neurological and psychiatric disorders. Anatomical Contrastive Learning (AnatCL) introduces anatomical contrastive learning strategies that enable effective representation learning from structural brain images without extensive manual annotations [36]. The model detects fine-grained anatomical differences valuable for complex diagnostic challenges. These include Alzheimer's disease (AD), autism spectrum disorder, and schizophrenia, where pathological changes may be subtle and spatially distributed.

CT FMs: Head CT interpretation in emergency settings represents a critical application where FMs provide immediate clinical value through rapid trauma assessment. Deep Comprehensive Neuro Trauma Detection Network (DeepCNTD-Net) introduces a specialized 3D FM for comprehensive neuro-trauma triage, leveraging LLMs for automatic multi-label annotation of 16 critical conditions including hemorrhage, mass lesions, cerebral edema, and arterial hyperdensity [78]. The model integrates task-specific pretrained networks for hemorrhage subtype segmentation and brain anatomy parcellation through multimodal fine-tuning, achieving an average AUC of 0.861 across all trauma conditions and outperforming CT-CLIP baselines. Training on 29,395 non-contrast head CT studies from nine international centers enables robust generalization capabilities, addressing the urgent need for AI-assisted interpretation in emergency radiology, where timely diagnosis is essential for optimal patient outcomes.

In parallel developments, FM for Head CT (FM-HCT) introduces a specialized 3D FM for comprehensive head CT disease detection in neurological emergency settings [55]. The model employs self-supervised learning on 361,663 non-contrast 3D head CT scans, utilizing discrimination with self-distillation and masked image modeling approaches with a customized 3D Vision Transformer architecture. The FM demonstrates substantial performance improvements, achieving 16.07% improvement in macro-AUC over models trained from scratch on internal data. Strong generalization across external datasets shows 20.86% and 12.01% improvements on NYU Long Island and RSNA datasets, respectively. Beyond traditional hemorrhage detection, the model extends capabilities to detect brain tumors, AD and related dementia, edema, and hydrocephalus. The model demonstrates effectiveness in few-shot learning scenarios and scales efficiently with increased pre-training data. This establishes a new benchmark for 3D head CT analysis, enabling broader deployment of AI-assisted diagnosis in emergency and clinical settings where rapid assessment is crucial for patient outcomes.

3.1.2 Electrophysiological Signal Processing Models

Large-scale AI models have substantially improved electrophysiological data analysis. These models address unique challenges in temporal dynamics, multi-channel spatial organization, and cross-subject variability in neural recordings.

EEG FMs: The development of transformer-based architectures for EEG analysis has been pioneered by several influential FMs that established the paradigm for large-scale neural signal processing. BENDR demonstrated the potential of self-supervised learning for EEG analysis through training on the extensive TUH EEG Corpus using Masked Signal Modeling and Contrastive Learning [9]. The transformer-based architecture enables effective transfer learning across diverse applications from sleep monitoring to brain-computer interfaces and disease detection. Fine-tuning evaluations on datasets including BCIC IV-2a, Sleep-EDF, and TUAB consistently demonstrate performance improvements over task-specific approaches.

Building on these foundations, emphasis on interpretability and transferability has advanced through large-scale pretraining approaches. EEGFormer extends the transformer paradigm by emphasizing performance and the ability to provide insights into temporal and spatial patterns that drive successful EEG classification [54]. This interpretability focus makes such models valuable for scientific discovery applications where understanding underlying neural mechanisms is as important as classification accuracy.

The adaptation of generative modeling principles to EEG analysis represents another significant advancement in the field. Neuro-GPT demonstrates how autoregressive architectures originally developed for natural language processing can be effectively adapted for EEG analysis. The model employs self-supervised pretraining followed by task-specific fine-tuning to achieve robust performance across multiple domains [39]. This autoregressive approach enables natural handling of variable-length EEG sequences while maintaining computational efficiency for real-time applications.

Comprehensive multitask learning capabilities have been developed through models that demonstrate exceptional versatility across diverse EEG applications. EEGPT advances this paradigm by showing that a single pretrained model can be effectively adapted to applications ranging from cognitive state classification to clinical diagnosis [79]. The model's architecture incorporates attention mechanisms specifically designed for EEG data characteristics, enabling robust transfer across different experimental paradigms and clinical conditions.

Specialized attention mechanisms designed for the unique temporal characteristics of EEG signals have emerged as critical innovations for specific applications. FM for EEG (FoME) introduces the ATLAS (Adaptive Temporal-Lateral Attention Scaling) mechanism, which enables dynamic adaptation to different temporal scales present in neural signals [80]. This approach proves effective for applications requiring precise temporal modeling, such as early seizure detection and advanced brain-computer interfaces, where millisecond-level accuracy can be crucial for clinical outcomes.

Recent developments in cross-scale spatiotemporal modeling have addressed a critical limitation inherited from NLP transformers: the inability to handle the multi-scale nature of neural activity. Cross-scale Spatiotemporal Brain foundation model (CSBrain) tackles this challenge through Cross-scale spatiotemporal tokenization that aggregates features from localized temporal windows and anatomical brain regions, combined with structured sparse attention to capture dependencies across different scales. Evaluated across 11 EEG tasks and 16 datasets, this approach consistently outperforms both task-specific models and existing FM baselines by explicitly modeling neural activity patterns ranging from millisecond-level spikes to multi-second cognitive processes [81].

The challenge of efficiently processing temporal and frequency domain information has been revolutionized through decoupled tokenization approaches. CodeBrain introduces a TFDual-Tokenizer that independently processes temporal and frequency components using separate codebooks, enabling quadratic expansion of discrete representation space compared to traditional linear approaches. This innovation, combined with Structured Global Convolution that reflects the small-world topology of the brain, demonstrates superior generalization capabilities across 10 public EEG datasets while maintaining computational efficiency for real-time applications [82].

Multimodal neural signal processing has emerged as a critical research area, with unified EEG-MEG analysis providing comprehensive insights into brain activity patterns. BrainOmni advances this field through training on 2,653 hours of combined neural data, implementing a novel BrainTokenizer architecture that incorporates sensor-specific encoding. This approach enables device-agnostic signal processing by independently encoding spatial configuration, sensor orientation, and modality

type, circumventing traditional naming convention dependencies. This unified training framework demonstrates measurable performance gains, achieving 20% improvement on EMEG SomatoMotor benchmarks compared to single-modality baselines. These results consistently validate the superiority of joint EEG-MEG training paradigms over isolated approaches [83].

Intracranial signal processing has progressed through disentanglement frameworks that isolate task-relevant neural components from background activity. BrainStratify implements a coarse-to-fine architecture integrating spatial-context modeling with Decoupled Product Quantization (DPQ) for sEEG and ECoG data analysis at millimeter resolution.The hierarchical processing pipeline effectively separates signal components while preserving spatial relationships across electrode arrays. Evaluation on speech production and perception datasets shows consistent superiority over existing intracranial decoding methods, with performance gains attributed to the systematic separation of task-specific neural patterns [84].

Emerging approaches in topology-agnostic processing and cross-view interaction frameworks continue to push the boundaries of EEG FMs. Latent Unified Network Architecture (LUNA) emphasizes computational efficiency and generalization across diverse electrode configurations, while Cross-View instance-adaptive Pre-training model (CRIA) introduces instance-adapted pre-training strategies for enhanced generalizable representations across subjects and experimental conditions [85, 86]. These developments reflect the field's continued evolution toward more flexible and adaptive neural signal processing architectures.

Advanced Neural Recording Models: FMs have extended to intracranial recordings, enabling detailed analysis of cortical neural dynamics. BRANT represents a significant advancement in this area, utilizing a 500-million-parameter architecture trained via masked patch prediction in a self-supervised framework [8]. The model addresses key challenges in sEEG data analysis, particularly the need for cross-patient generalization and spatial precision. Training on large-scale intracranial datasets enables robust performance across diverse recording configurations and experimental paradigms. The architecture proves especially effective for decoding tasks requiring millisecond temporal resolution and the spatial specificity inherent to intracranial electrode placement, demonstrating improved generalization compared to traditional patient-specific approaches.

Cross-modal integration of surface and intracranial recordings addresses the critical challenge of translating findings across recording modalities. BrainWave achieves this through a unified architecture that processes both EEG and IEEG data within a single framework [87]. The cross-modal training enables transfer learning between surface and intracranial modalities, facilitating knowledge transfer from high-resolution invasive studies to non-invasive clinical settings. This approach directly addresses the translation gap between detailed mechanistic insights obtained from intracranial recordings and their application to broader patient populations limited to surface recordings. The unified framework demonstrates that FMs can effectively bridge spatial resolution differences while preserving relevant neural information across modalities.

Specialized EEG Applications: FMs have demonstrated particular effectiveness in specialized EEG applications through domain-specific pretraining strategies. Adaptive Large Foundation model for EEG signal representation (ALFEE) addresses key limitations in EEG foundation modeling, including variable channel configurations, inadequate separation of spatial and temporal features, and domain transfer challenges [88]. The architecture implements a hybrid transformer design with distinct channel-wise and temporal attention mechanisms, enabling robust processing across diverse electrode configurations. A two-stage optimization incorporates comprehensive pretraining objectives—task prediction, channel reconstruction, temporal reconstruction, and forecasting—followed by adaptive fine-tuning using task-specific token dictionaries and cross-attention. Evaluation across six downstream tasks, including emotion recognition, sleep staging, and abnormality detection, demonstrates superior performance over existing multi-task EEG models. Scaling analysis on models up to 540M parameters trained on 25,000 hours of EEG data confirms consistent performance gains with increased scale, establishing a foundation for large-scale EEG model development.

Masking strategy adaptation to neural signal characteristics has proven critical for FM performance. Large Brain Model (LaBraM) demonstrates this principle by tailoring masked modeling approaches to EEG temporal dynamics, achieving superior results compared to direct application of computer vision masking techniques [89]. The domain-aware pretraining strategy accounts for the unique temporal structure of neural signals, highlighting the importance of signal-specific architectural considerations in FM design.

FMs have demonstrated significant potential in neurodegenerative disease detection through specialized clinical applications. The large-scale foundation model for EEG-based AD detection (LEAD) addresses Alzheimer's diagnosis via subject-level detection that incorporates domain knowledge of neurodegenerative progression [90]. The architecture maintains robust diagnostic accuracy across stages, demonstrating effective incorporation of stage-consistent representations into FM frameworks for reliable performance in clinical applications where diagnostic precision is critical.

3.1.3 Multimodal Integration Approaches

Neuroscience AI models are progressing toward multimodal integration to enable comprehensive brain function analysis. These approaches combine spatial, temporal, and semantic information across diverse neural recording modalities, leveraging complementary data sources for enhanced understanding of neural mechanisms.

Cross-Modal Brain Decoding: Vision-language models have been adapted for neuroscience applications to decode visual processing mechanisms. MindBridge integrates fMRI data with visual and semantic information through representation alignment strategy that utilize CLIP embeddings for cross-subject generalization [15]. Training on the Natural Scenes Dataset (NSD) demonstrates effective representation transfer across subjects, addressing cross-subject variability in neuroimaging and establishing scalable approaches for brain decoding tasks.

The Bridging-Vision-and-Language (BriVL) model establishes a large multimodal FM jointly pre-trained on 15 million image–text pairs [91]. It learns shared visual–linguistic representations that enable cross-modal prediction and generalization. Neural encoding analyses using fMRI demonstrate strong alignment between BriVL's multimodal representations and human brain activity patterns, suggesting that multimodal FMs can serve as computational tools for studying multisensory integration and cognition.

Recent advances in brain-vision-language integration have focused on leveraging pre-trained models for neural decoding. BrainCLIP utilizes CLIP's multimodal representations to decode natural visual stimulus from neural activity, bridging the semantic gap between neural signals and visual understanding [37]. The approach enables decoding of complex, naturalistic visual stimuli by training a mapping network that aligns fMRI patterns with CLIP's unified embedding space, advancing beyond traditional methods limited to simple, controlled stimuli. This demonstrates the potential for FMs as cross-modal translators, suggesting that semantic representations from large-scale pre-training capture fundamental information processing principles relevant to biological neural systems and provide new directions for neuroscience research.

Integration of language and brain function: The End-to-end Multimodal LLM achieves direct language decoding from neural signals by adapting LLM architectures for fMRI-to-text translation [92]. Specialized pretraining and fine-tuning enable direct textual decoding from fMRI sequences, advancing toward natural language brain-computer interfaces. This approach represents a significant step in bridging neural activity and linguistic output through end-to-end learning frameworks. Integration of language modeling with neuroimaging demonstrates FMs' capacity to bridge neural activity and semantic understanding for natural brain-computer communication. Success in extracting linguistic information from neural signals indicates potential applications in assistive technologies for communication disorders, enabling direct neural-to-text interfaces that could restore communication capabilities in clinical populations.

Structural-Functional Integration: Recent studies have focused on integrating structural and functional brain data through large-scale AI models to enhance diagnostic capabilities. MultiViT introduces a multimodal vision transformer that fuses 3D gray matter maps from structural MRI with functional network connectivity (FNC) matrices derived from ICA-processed fMRI using cross-attention mechanisms [38]. The architecture achieves an AUC of 0.833 in schizophrenia classification, outperforming unimodal and concatenation-based approaches. By replacing high-dimensional fMRI data with lightweight two-dimensional FNC representations and employing separate 3D and 2D vision transformer encoders with cross-attention fusion, MultiViT effectively captures structure-function relationships. The interpretability framework generates attention maps identifying neurobiologically meaningful regions in 3D structural space, providing insights into disease-relevant patterns in brain areas such as the cerebellum, temporal gyrus, and prefrontal regions. This establishes a paradigm for efficient multimodal neuroimaging analysis that bridges anatomical organization with functional dynamics in psychiatric disorders, demonstrating that advanced fusion mechanisms like cross-attention

are essential for optimal performance while maintaining computational efficiency.

Table 4: Comprehensive Overview of Large-scale AI Models for Computational Neuroscience Research. (PT: Pre-training; FT: Fine-tuning)

Model Name	Primary Purpose/Application	Model Type	Training Method	Dataset Used
ADAgent [93]	Alzheimer's disease analysis	Framework w/ LLM	LLM integration	ADNI dataset (T1-MRI, PET-FDG)
ALFEE [88]	General EEG representation learning for multiple tasks	FM	PT + FT	Multi-task EEG datasets including clinical, emotion, sleep, and work-load
AnatCL [36]	Anatomical FM for structural brain MRI analysis	FM	PT + FT	Multiple MRI datasets with Desikan-Killiany atlas
ASD-Chat [94]	Autism spectrum disorder support	Framework w/ LLM	Prompt-based	Clinical intervention data
AtlasGPT [40]	Neurosurgical clinical augmentation	LLM	RAG-enhanced LLM	JNSPG articles
BENDR [9]	Transformer-based EEG analysis for BCI applications	FM	PT + FT	TUEG and other large EEG datasets
BRANT [8]	FM for intracranial neural signal analysis	FM	PT + FT	Large corpus of intracranial SEEG data
BrainBench [95]	Neuroscience benchmarking framework	LLM	PT + FT	Neuroscience literature
BrainCLIP [37]	Task-agnostic fMRI brain decoding with CLIP integration	Framework w/ LLM	PT + FT	fMRI data with visual stimuli
Brain-Diffuser [16]	fMRI-to-image reconstruction using generative diffusion	FM	PT + FT	Natural Scenes Dataset (NSD)
BrainGFM [45]	Unified framework for large-scale fMRI pre-training	FM	PT + FT	27 datasets, 25,000+ subjects, 60,000 fMRI scans
BrainGPT [96]	Neurosurgical applications	LLM	PT + FT	1.3B tokens (neuroscience literature)
BrainIAC [77]	General-purpose FM for structural brain MRI	FM	PT + FT	48,519 brain MRIs from 35 datasets
BrainLM [56]	FM for brain activity dynamics prediction	FM	PT + FT	UK Biobank, HCP (80,000 scans, 40,000 subjects)
BrainOmni [83]	First FM for unified EEG and MEG analysis	FM	PT + FT	1,997 hours EEG + 656 hours MEG
BrainSegFounder [35]	3D FM for multimodal neuroimage segmentation	FM	PT + FT	UK Biobank (41,400 participants), BraTS, ATLAS v2.0
BrainStratify [84]	FM for invasive and non-invasive recordings	FM	PT + FT	40,000+ hours electrical brain recordings
BrainWave [87]	FM for invasive and non-invasive recordings	FM	PT + FT	40,000+ hours electrical brain recordings
BriVL [91]	Multimodal FM bridging vision and language	FM	PT + FT	RUC-CAS-WenLan (30M image-text pairs), fMRI data
CBraMod [33]	EEG decoding for BCI applications	FM	PT + FT	TUEG (1.1M samples, 9000+ hours)
Centaur [52]	Human behavior prediction	FM	PT + FT	Psych-101 (60K+ participants)
CodeBrain [82]	EEG foundation model for interpretable decoding	FM	PT + FT	TUH EEG Corpus for pretraining and multiple EEG cohorts for downstream tasks.
CSBrain [81]	Cross-scale spatiotemporal brain FM for EEG	FM	PT + FT	11 EEG tasks across 16 datasets
DeepCNTD-Net [78]	3D FM for multi-label neuro-trauma detection on non-contrast head CT scans.	FM	PT + FT	Non-contrast head CT images
DECT [48]	LLM-driven model extracting linguistic markers and synthesizing dialogue data for Alzheimer's diagnosis.	Framework w/ LLM	PT + FT	Speech recording and transcripts from ADReSSo (from Dementia-Bank)
EEGFormer [54]	Large-scale EEG FM for transferable learning	FM	PT + FT	TUH Corpus (1.7TB EEG dataset)
EEGPT (v1) [79]	Generalist EEG FM for multiple tasks	FM	PT + FT	37.5M pre-training samples, 1B tokens
EEGPT (v2) [79]	Universal EEG feature extraction for medical and BCI	FM	PT + FT	Large mixed multi-task EEG dataset
EpiSemoLLM [97]	Epileptogenic zone localization	LLM	PT + FT	Collected seizure semiology descriptions
ExKG-LLM [98]	Cognitive neuroscience knowledge graph expansion	Framework w/ LLM	LLM-KG integration	Scientific papers and clinical reports
FM-HCT [55]	3D FM for head CT disease detection	FM	PT + FT	361,663 non-contrast 3D head CT scans
FoME [80]	FM for EEG with adaptive attention scaling	FM	PT + FT	1.7TB diverse scalp and intracranial EEG
Hmamouche et al. [92]	Non-invasive decoding of spoken text from fMRI	Framework w/ LLM	PT + FT	Custom corpus with fMRI recordings
HybridTransNet [47]	Brain tumor boundary delineation	Framework w/ LLM	PT + FT	Medical imaging datasets
iReportMed [99]	Hybrid pipeline: CNN extracts multi-modal MRI features; LLM generates structured brain tumor diagnostic.	Framework w/ LLM	PT + FT	˜378 brain tumor MRI scans (350 UCSF-PDGM + 28 clinical cases)
LaBraM [89]	Large brain model for generic EEG representations	FM	PT + FT	˜2,500 hours EEG from 20 datasets
LEAD [90]	Clinical applications in neurodegenerative disease detection	FM	PT + FT	Alzheimer's disease related EEG datasets
LUNA [85]	Topology-agnostic EEG processing with computational efficiency	FM	PT + FT	Diverse electrode configurations
Mental-LLM [49]	LLM (GPT-based) fine-tuned to predict mental health status from online textual posts.	Framework w/ LLM	PT + FT	Online text (social media data)
MindBridge [15]	Cross-subject brain decoding for visual reconstruction	FM	PT + FT	Multiple subjects' fMRI with visual stimuli
MindEye [73]	fMRI-to-image reconstruction using contrastive learning	FM	PT + FT	Natural Scenes Image–fMRI Dataset (8 subjects)
MindEye2 [34]	Efficient fMRI-to-image with minimal training data	FM	PT + FT	Natural Scenes Image–fMRI Dataset (7 subjects)
MinD-Vis [53]	Visual stimulus decoding from fMRI using diffusion	FM	PT + FT	˜136,000 fMRI samples, 1,205 subjects
MsLesionLLM [100]	LLM-based prompt classifying MRI reports to extract new MS lesion information.	LLM	PT + FT	Clinical MRI report text
MultiViT [38]	Structural-functional brain data integration for schizophrenia diagnosis	FM	PT + FT	Multi-site MRI (2,130 subjects)
MDD-LLM [101]	Major depressive disorder diagnosis	LLM	PT + FT	UK Biobank (274,348 records)
Neura [102]	Specialized neurology applications	LLM	PT + FT	Neurological corpus
Neuro-GPT [39]	FM for EEG-based BCI tasks	FM	PT + FT	TUH EEG Corpus, BCI Competition IV 2a
NeuroGPT-X [103]	Neurosurgical decision support	LLM	RAG-enhanced LLM	PubMed abstracts, Wikipedia
NeuroPictor [76]	fMRI-to-image reconstruction with semantic control	FM	PT + FT	67,000 fMRI-image pairs

Model Name	Primary Purpose/Application	Model Type	Training Method	Dataset Used
LaMIM [104]	Postencephalitic epilepsy analysis using multi-contrast brain MRI	FM	PT + FT	57,621 multi-contrast whole-brain MRI
PKG-LLM [105]	Mental health prediction (GAD/MDD)	Framework w/ LLM	LLM-KG integration	NeuroLex, NeuroMorpho databases
POYO [106]	Spike-based neural decoding	FM	PT + FT	158+ sessions, 27,373+ neural units
ProMind-LLM [107]	Psychiatric evaluation	LLM	PT + FT	PMData and Globem datasets
scFoundation [108]	Single-cell transcriptomics representation learning	FM	PT + FT	Multiple single-cell RNA-seq datasets
SHADE-AD [46]	LLM framework generating synthetic Alzheimer's-specific human activity videos to augment monitoring datasets.	Framework w/ LLM	Prompt-based	NTU RGB+D 120 dataset (over 120,000 videos).
SocialRecNet [109]	Multimodal LLM (speech+text) framework predicting ASD social reciprocity scores from conversational data.	Framework w/ LLM	LLM integration	Speech and text for autism spectrum disorder
TRUST [110]	LLM-powered dialogue system of cooperative modules for structured PTSD diagnostic interviews.	Framework w/ LLM	LLM integration	Text (clinical interview dialogues)
VS-LLM [51]	Vision-language LLM analyzing therapy sketches for depression assessment.	LLM	PT + FT	PPAT drawing test (sketches + stroke sequences)

3.2 Brain-Computer Interfaces and Neural Decoding

Brain-computer interfaces represent one of the most promising applications of large-scale AI models in neuroscience, where the ultimate goal is to establish direct communication pathways between the brain and external devices. FMs have revolutionized this field by enabling robust neural signal decoding across subjects, sessions, and recording modalities with unprecedented accuracy and generalization capabilities. The development of specialized architectures for real-time neural decoding has led to remarkable achievements in motor intention prediction, cognitive state classification, and direct neural control of external devices.

Brain-Computer Interface Models: The application of large-scale AI models to brain-computer interfaces has been driven by the need to overcome fundamental challenges in neural signal decoding, including limited labeled data and high inter-subject variability that traditionally hamper BCI performance. Self-supervised pretraining approaches have emerged as particularly effective solutions, enabling models to learn robust neural representations from large amounts of unlabeled data before fine-tuning on specific BCI tasks. Specialized architectures designed for BCI applications have demonstrated that domain-specific innovations can significantly enhance decoding performance. CBraMod exemplifies this approach through its innovative criss-cross transformer architecture designed for large-scale EEG decoding and BCI applications [33]. Its dual spatial-temporal attention mechanism effectively captures heterogeneous dependencies in EEG signals, while self-supervised pretraining on the Temple University Hospital EEG Corpus followed by fine-tuning across 10 downstream BCI tasks achieves robust generalization and superior decoding accuracy, even in low-data regimes.

Transformer-based architectures demonstrate versatility for BCI applications through general-purpose models with broad task adaptability. BENDR employs transformer architecture with contrastive self-supervised learning for effective transfer learning across motor imagery classification and attention state detection [9]. The model learns robust representations from large unlabeled EEG datasets, addressing the challenge of limited subject-specific labeled data in BCI scenarios and demonstrating successful adaptation of general FMs to specialized applications. Advanced temporal modeling has become critical for real-time BCI performance, requiring precise timing and dynamic adaptation to neural signal characteristics. FoME addresses this through the ATLAS mechanism, enabling dynamic adaptation across different temporal scales in neural signals [80]. This capability proves valuable for complex BCI applications requiring sustained attention and motor control, where capturing both short-term neural dynamics and long-term cognitive patterns enables robust real-time performance across diverse BCI paradigms.

High-Resolution Neural Decoding Models: FMs for high-resolution neural recordings represent a frontier in brain-computer interface research, enabling precise decoding of individual neuronal activity patterns. Pre-training On manY neurOns (POYO) introduces spike-based tokenization for processing high-resolution neural recordings, directly processing individual spike events as discrete tokens rather than binned neural data [106]. This approach preserves the neural code's temporal structure while maintaining computational efficiency through sparse representation. The transformer architecture employs a PerceiverIO backbone with cross-attention mechanisms to compress spike sequences into latent representations, enabling scalable training across multiple sessions without requiring neu-

ron correspondence. POYO addresses the challenge of integrating neural recordings across individuals with unique, non-alignable neuron sets. Training encompasses 178 recording sessions with 29,453 neural units from motor, premotor, and somatosensory cortices across 9 nonhuman primates, totaling over 100 hours of recordings. The "unit identification" approach enables rapid adaptation to new sessions by freezing pretrained weights and learning unit embeddings through gradient descent, achieving few-shot learning performance comparable to models trained from scratch with minimal labeled data. POYO demonstrates superior neural decoding performance with R^2 scores of 0.95 on center-out reaching tasks and 0.87 on complex random target tasks, while supporting real-time processing for closed-loop BCI applications.

3.3 Molecular Neuroscience and Genomic Modeling

Current advances in neuroscience increasingly emphasize the need to address brain function not only at the systems and behavioral levels, but also through the molecular and genetic mechanisms that control neural activity and disease. On the molecular front, FMs, trained on large genomic and transcriptomic datasets, are transforming our ability to solve for the regulatory architecture of the genome and its impact on neuronal processes. These models introduce the representation learning paradigm into the DNA and RNA domains and allow for computational prediction of gene regulation, variant effect, and cell-type-specific function.

The Nucleotide Transformer comprises multiple FMs pre-trained on 3,202 diverse human genomes, and 850 genomes from various species with between 500 million and 2.5 billion parameters [111]. The models can predict chromatin states, enhancer-promoter interactions, and transcription factor binding sites, despite the small proportion of DNA sequences containing transcription factor motifs. Similar FMs, including AlphaGenome [41] and Enformer [42] and which are trained on DNA sequences, are enabling the prediction of the functional consequence of genetic variation in the regions of DNA that do not encode proteins. Tools for annotating the protein-coding regions of the DNA are well established and enable reliable prediction of how genetic variants affect proteins. In contrast, a poor understanding of non-protein-coding DNA, where most of the disease-associated variation lies, has long hindered progress in genomic research. FMs are now transforming this landscape by enabling scientists to prioritise variants for research question-specific modelling. Similarly, the scFoundation model that was pretrained on over 50 million single-cell RNA sequencing data to model 19,264 genes with 100 million parameters, is one of several models that exploit growing repositories of transcriptomic data to provide rich contextual maps of cell function, under both normal and pathological conditions [108], transforming our capacity to predict both function and dysfunction.

Collectively, these FMs hold considerable promise for neuroscience research, as they can be leveraged to study neuronal gene regulation, characterize diverse neural cell types, and investigate the molecular basis of neurological diseases and brain function at an unprecedented scale.

3.4 Clinical Support and Translational Frameworks

Scalable AI systems, especially FMs, are being used at a greater rate in clinical neuroscience to aid diagnostic decision support and enhance patient outcomes in psychiatric and neurological practice. These translational systems are required to overcome a number of key challenges: providing adequate clinical validation, preserving interpretability for clinicians, and blending with current clinical practice. These implementations should also meet regulatory requirements and handle ethical issues involved with medical AI use.

3.4.1 Clinical Decision Support

Neuroscience clinical decision support systems are being transformed through the integration of LLMs that support physicians with diagnosis, treatment guideline formulation, and patient care. With the use of expansive medical knowledge databases and clinical databases, the AI systems yield evidence-based advice and improve diagnostic efficacy. The technology has a specific forte in facilitating sophisticated clinical reasoning both in neurological and psychiatric domains and offers clinicians advanced mechanisms of decision-support while dealing with complex patient situations and treatment modalities.

Specialized Neurological Decision Support Systems: Various FMs have been uniquely designed to tackle intricate neurological disorders that necessitate specialized clinical knowledge.

EpiSemoLLM exemplifies a focused methodology for managing epilepsy by utilizing refined language models that analyze descriptions of epilepsy semiology alongside optional demographic attributes to forecast epileptogenic zones (EZs) [97]. This model is trained on extensive datasets sourced from PubMed literature and proprietary electronic health record groups, facilitating accurate localization of seizure origins to inform surgical planning and therapeutic strategies. NeuroGPT-X presents context-enhanced language models of neurosurgical decision support with zero-shot learning models involving GPT-3 API interfacing [103]. Clinical-specific functionalities such as conversation memory, in-text citation, reference, medical topic limitation, timestamping, and anti-spam are part of the system. Testing with international neurosurgical experts on vestibular schwannoma treatment queries revealed similar clinical reasoning and treatment advice performance and proved the feasibility of AI-augmented neurosurgical advice.

Advanced Clinical Augmentation Platforms: With the advent of sophisticated clinical augmentation systems comes the support of advanced features of neurological practice. AtlasGPT represents a RAG LLM designed for neurosurgical applications, integrating generative reasoning with domain-specific literature retrieval to enhance the accuracy and reliability of clinical insights [40]. Trained on 250,000 pages of peer-reviewed neurosurgical data, the system provides contextualized recommendations for surgical planning, decision-making, and educational support, illustrating the potential of specialized LLMs to augment clinical practice. Furthermore, Neura introduces a specialized LLM solution for clinical neurology, combining RAG with tailored prompt engineering to enhance contextual relevance and verifiable information synthesis [102]. Its dual-database architecture and emphasis on explainability highlight the importance of human–AI interaction design in clinical decision support systems.

Comprehensive Clinical Decision Support Paradigms: Almanac provides multi-specialty clinical decision support using RAG language models that couple medical corpus pretraining with advanced prompt engineering [112]. The system retrieves relevant medical literature and guidelines to produce contextually grounded recommendations for complex clinical questions. This approach allows healthcare providers to access synthesized medical knowledge and evidence-based insights in real time, reducing diagnostic uncertainty and improving decision confidence. Such RAG frameworks exemplify the broader promise of FMs to advance neurological and psychiatric practice by delivering specialized expertise, minimizing diagnostic error, and facilitating evidence-based treatment selection. Integration of RAG, domain-specific pretraining, and streamlined human–AI interaction design offers a promising direction for the evolution of AI-augmented clinical decision support.

Comprehensive Neuroscience Benchmark and Assessment: BrainBench provides a standardized framework for evaluating language models in neuroscience through an open, CC-BY-licensed benchmark dataset [95]. In a systematic approach, this strategy presents standardized tests to probe the capabilities of AI models on a wide range of neuroscience tasks and enables rigorous comparison of diverging modeling methods while indicating areas where current AI systems excel or require improvement. An open license-based focus of the framework ensures reproduction and broad accessibility to the research community.

Automated Construction and Expansion of Knowledge Graphs: Automated knowledge extraction tools have revolutionized neuroscience knowledge utilization and organization. ExKG-LLM demonstrates the application of LLMs to the automatic expansion of cognitive neuroscience knowledge graphs (CNKG) [98]. By combining advanced information extraction, probabilistic link prediction, and prompt-engineering-based integration, the framework systematically identifies and incorporates entities and relations from extensive neuroscience literature. This automated process enhances the accuracy, completeness, and structural richness of cognitive neuroscience knowledge graphs, facilitating deeper scientific discovery and reasoning in the field. Expanding upon such foundational capabilities, PEIRCE unifies material and formal inference through an iterative conjecture–criticism process [113]. This neuro-symbolic framework provides a conceptual foundation for interpretable reasoning in neuroscience, where empirical data and theoretical hypotheses can be jointly evaluated.

Clinical Prediction and Mental Health Modeling: In addition to Beyond knowledge extraction, large-scale AI models are increasingly applied to clinical prediction. PKG-LLM exemplifies this integration by combining cognitive neuroscience knowledge graphs with LLMs to predict and differentiate Generalized Anxiety Disorder (GAD) and Major Depressive Disorder (MDD) [105]. By merging structured neurobiological ontologies with unstructured clinical text through GPT-4–based entity extraction and expert validation, the model enhances diagnostic precision and interpretability,

underscoring the potential of AI-driven systems to advance early detection and intervention in mental health.

Prediction of Human Behavior and Cognitive Modeling: In cognitive modeling, Centaur proposes a FM approach for the prediction of human behavior through training on the Psych-101 dataset with the use of supervised learning and fine-tuning methods [52]. The model extends the understanding of cognitive processes of humans through learning the ability to predict behavioral outcomes under a wide range of psychological tasks and scenarios. The system's skill at modeling patterns of human decision-making offers substantial contributions towards cognitive mechanisms and provides valuable use cases towards the creation of humanity-focused AI systems.

Integration of Neurosymbolic and Feature Extraction: Neuro-Symbolic GPT (NeSyGPT) contributes towards neurosymbolic AI by further tuning vision–language FMs to automatically extract symbolic features from raw neuroimaging data [50]. This enables the efficient integration of low-level neural metrics with high-level cognitive constructs through the automatic generation of interpretable symbolic representations. By combining the capabilities of base models with symbolic reasoning, NeSyGPT yields more understandable and interpretable AI systems for neuroscience applications. Such cognitive modeling and knowledge-driven AI techniques demonstrate the capacity of FMs to enrich computational neuroscience through automated knowledge extraction, behavioral prediction, and unified neurosymbolic frameworks. Through broad pre-training, task-specific fine-tuning, and prompt engineering, these systems can advance our understanding of brain function and cognitive processes while supporting clinically relevant assessment and intervention tasks.

3.5 Disease-Specific Applications

Disease-specific neuroscience investigations have increasingly utilized large-scale AI models with notable promise for brain disorder diagnosis and treatment. These models play dual functions as primary computational engines of diagnostic and treatment tasks and as auxiliary components of broader clinical systems. Current assessments offer illustrative support of this promise with investigations such as Luo et al.'s systematic assessment of ChatGPT applied to epilepsy presurgical decision-making, offering insight that complex seizure semiology could be accurately interpreted with LLMs as a component of critical clinical decision-making [114]. Utilization has involved direct utilization of pre-trained models for classifying diseases, fine-tuning condition-specialized architecture for condition-specific tasks, and incorporating language models into clinical decision support systems with enhanced diagnostic accuracy and treatment planning.

Clinical usefulness goes beyond general diagnostic purposes, as evidenced by extensive neurological tests where ChatGPT-4 obtained passing scores on neurology-specialized tests with no neurology-specialized training and exceeded human means in cognitive exercises [115, 116]. LLMs were also demonstrated to outperform neuroscience experiment outcome predictions made by human experts using the BrainBench benchmark, indicating scientific discovery and hypothesis generation capabilities [95]. Large-scale AI model versatility allows one to use wide knowledge bases while flexibly tuning towards particular disease domain needs and produce accurate, efficient, and clinically appropriate AI-enabled healthcare solutions with transformative promise for enhanced diagnostic precision, treatment individualization, and patient outcomes in neurological and psychiatric disorders.

3.5.1 Neurodegenerative Disorders

Neurodegenerative conditions pose special challenges to AI-augmented diagnosis and treatment because of their continuous nature and intricate pathophysiology. Large AI systems have demonstrated excellent strides in the treatment of AD dementia, Parkinson's disease, and multiple sclerosis through specially crafted architecture and domain-specific training methods that reflect biomarkers and course patterns specific to the disease.

While AI methods have achieved remarkable performance in discrete classification tasks such as early detection, diagnosis (e.g., AD vs. non-AD), and predicting conversion to dementia [117, 118, 119, 120], their application to continuous and fine-grained prognostic measures remains limited. Predicting gradual trajectories of neurological and cognitive decline demands models capable of capturing subtle temporal and physiological variations, rather than merely performing binary classification. Current approaches have shown only modest success in this regard—for instance, models trained on neuroimaging

data often struggle to accurately estimate cognitive scores over time [121]. Similarly, transfer learning based on a pretrained ResNet50 model achieved reliable conversion prediction but exhibited weak correlations with actual cognitive decline [122]. Addressing these challenges is crucial for advancing AI's role in clinical settings and for deepening our understanding of fundamental questions in the neuroscience of dementia [123], such as how neural signal features map onto higher-order cognitive processes.

ADAgent is an LLM-driven conversational system for Alzheimer's Disease support, using multi-turn interaction to coordinate multimodal diagnostic tools and reasoning-driven clinical assessment [93]. It adapts its guidance to cognitive impairment levels and facilitates early-stage monitoring and decision support. Supporting this direction, DECT demonstrates advanced diagnostic capability for speech-based Alzheimer's Disease detection by leveraging LLM-assisted fine-grained linguistic representation and label-switched / label-preserved data generation to improve transformer-based classification performance [48].

Also of notable relevance to Alzheimer's research is the Synthesizing Human Activity Datasets Embedded with AD Features (SHADE-AD) framework, which generates AD-specific human activity datasets through a three-stage LLM-assisted training pipeline that embeds subtle motor and behavioral signatures of the disease [46]. Rather than integrating clinical biomarkers, SHADE-AD focuses on synthesizing realistic AD-characteristic body movement patterns, and uses joint-level motion metrics to ensure fidelity, enabling downstream models to achieve improved recognition performance in smart-health AD monitoring scenarios. Providing broader foundations for the research community, findings of Gao et al. cover an extensive analysis of LLM applications at neurodegenerative disorders with standardized benchmarking and assessment frameworks of AI-based systems at this spectrum of disorders while overcoming disparities such as heterogeneity of data, clinical interpretability, and regulatory issues [124]. In multiple sclerosis applications, MsLesionLLM targets lesion detection and course of the disease monitoring with language model techniques that combine natural language processing of clinical notes and computational interpretation of MRI findings with an aim of monitoring the course of the disease and treatment response longitudinally [100]. The system takes advantage of domain-specific terminologies and clinical patterns of reasoning with an aim of providing an appropriate measure of lesion burden and course of disability metrics.

3.5.2 Acquired Neurological Disorders

Acquired neurologic disorders that arise from external trauma, vascular occurrences, or pathologic processes demand advanced diagnostic methods and timely treatment mechanisms and are thus prime candidates for AI-enhanced clinical support systems. Such neurologic disorders also present intricate patterns of symptom presentations susceptible to high-scale AI systems with sophisticated pattern recognition features and real-time analytics, and with heterogeneous clinical databases trained.

As a complex and heterogeneous condition requiring accurate and timely diagnosis and management, involving vast data across multiple modalities (i.e., clinical, EEG, video, neuroimaging, genomics), epilepsy is a perfect use case for large-scale AI models across the entire clinical pathway—from detection and diagnosis to localization, risk prediction, and personalized treatment optimization.

Video-based seizure detection presents an important avenue for improved epilepsy diagnosis and classification. SETR-PKD is a novel framework that utilises a transformer-based progressive knowledge distillation and encodes seizure motion semiotics from raw RGB videos by extracting optical flow features, thus importantly preserving the privacy of the patient. This model can detect tonic-clonic seizures with an accuracy of 83.9% in a privacy-preserving manner [43]. VSViG is another novel video-based seizure detection model that applies transformer architecture in the form of a skeleton-based spatiotemporal Vision Graph, outperforming previous state-of-the-art approaches in detecting focal or generalised tonic-clonic seizures, and importantly, doing so while utilising fewer parameters and computing power [44]. Given that traditional EEG approaches to seizure detection and classification are resource-intensive and mostly non-portable, these approaches pave the way for increased methods of seizure detection, including in an ambulatory setting.

Beyond detection, accurate seizure classification is critical for treatment planning. EpilepsyLLM represents a special-purpose system for seizure diagnosis and treatment, combining intricate seizure semiology description analysis with patient demographics and EEG pattern classification to yield seizure type prediction and treatment protocol optimization [125]. It utilizes sophisticated natural language processing of clinical narrative texts and textual description-electrophysiology correspondence

classification towards complete characterization of epilepsy.

Going one step further in epilepsy management, EpiSemoLLM offers a fine-tuned dedicated language model applying seizure semiology description analysis alongside demographic attributes as an aid towards epileptogenic zone (EZ) prediction [97]. Having undergone training with extensive datasets retrieved from PubMed publications and individual electronic health records cohorts, the model shows an advanced level of seizure semiology terminology knowledge and the ability to associate intricate symptom descriptions with anatomical localisation. In this manner, more specific seizure origin identification becomes possible with valuable input towards surgical planning and medication optimization during treatment of medication-resistant seizures, where a successful treatment outcome entails proper EZ localization.

While these models address diagnosed epilepsy, FMs also enable risk prediction in at-risk populations. Vision FMs have applications in predicting epilepsy development. Gao et al have developed a large self-supervised vision FM to assess the occurrence of epilepsy after encephalitis. Trained on over 57,000 whole-brain MRI scans, the model outperformed older, task-specific, pre-trained models in predicting the occurrence of post-encephalitic epilepsy, with the affected anatomical brain regions shown to be of importance in informing the model's decisions in this classification task [104]. Such prediction models allow for appropriate risk-stratification, earlier intervention in high-risk individuals, and in turn, better treatment outcomes for these patients.

Following diagnosis and risk stratification, treatment selection remains a critical challenge. Antiseizure medications (ASMs) successfully treat patients diagnosed with epilepsy. Selecting which medication is best for a patient, however, often requires a trial-and-error approach, and approximately a third of patients fail to respond to these medications. Deep learning models that can predict individual response to a drug are being developed and evaluated in the clinical setting [126]. Models that reason over clinical and genetic patient information [127, 128, 129] can improve performance over those trained on clinical characteristics alone [130]. More extensive multimodality models that include, for example, EEG and MRI will further enable personalised care in epilepsy.

Stroke treatment is another key application case, where Song et al. discuss extensive analysis frameworks with LLMs for expedited assessment and treatment planning and combining clinical presentations with neuroimaging results to aid time-critical decision-making during acute stroke treatment [131]. The system merges multimodal data integration with clinical reasoning functions to forecast stroke outcomes and tailor intervention methods. In a more expansive context, Kottlors et al. discuss LLM deployments across a wide range of neurological disorders and shed light on general-purpose AI systems adaptable across differing neurological presentations yet with high accuracy and clinical relevance [132].

3.5.3 Brain Tumors and Structural Abnormalities

Surgery planning and brain tumor diagnosis are prime use areas where AI accuracy has a disproportionate impact on patient outcomes through improved diagnostic accuracy, optimized treatment, and surgical navigation. Large-scale AI systems capitalize on state-of-the-art neuroimaging analysis, high-accuracy surgical planning, and computerized clinical reporting systems that streamline the efficiency of radiological workflow.

Multimodal FM methods of brain tumor classification are enhanced by Manjunath et al., who combine high-resolution neuroimaging features with clinical features, genomic features, and histopathological features to allow for complete tumor description and prediction of prognosis [133]. The model utilizes high-level feature fusion methods and attention mechanisms to identify intricate associations among imaging phenotypes and molecular subtypes. Moreover, new architecture designs are proposed with HybridTransNet that integrate convolutional neural network feature extraction with attention mechanisms from the transformer architecture with the aim of obtaining accurate tumor boundary delineation and volumetric analysis of several MRI sequences [47]. The model also utilizes uncertainty quantification and yields confidence scores for quality assessment of the segmentation. Besides, neurosurgical conversational AI systems are created using BrainGPT, where LLMs are trained from a fine-tuning of neurosurgical texts and clinical guidelines to issue evidence-based guidelines for surgical methods, risk evaluation, and postoperative treatment planning [96]. Expanding clinical use further, Ma et al. illustrate large-scale language model use in cerebral tumor treatment and treatment planning with an emphasis on automated clinical guideline synthesis, optimization of treatment protocols, and individualized therapy advice with tumor and patient variables [134]. The reporting sys-

tems are automated under iReportMed through the use of natural language generation capability that produces well-formatted radiology reports with important findings highlighted, differential diagnosis stated with pertinent follow-up recommendations while maintaining clinical accuracy and regulatory compliance [99].

3.5.4 Major Psychiatric Disorders

Understanding psychiatric disorders takes more than just measuring biomarkers, as it requires a careful look at how people behave, the symptoms they show, and how they respond to treatment. In this space, large-scale AI models are beginning to help by using natural language processing, behavioral data from different sources, and long-term health records to make diagnoses more accurate and guide more personalized treatment plans.

Targeting major depressive disorder specifically, MDD-LLM employs fine-tuned large language models trained on large-scale real-world tabular health data from the UK Biobank, where structured features are converted into natural-language prompts for supervised diagnosis [101]. Rather than sentiment modeling or conversational transcripts, the system leverages feature-driven risk estimation, probability-based outputs, and explainable reasoning to enhance diagnostic accuracy and clinical interpretability.

VS-LLM (Visual-Semantic LLM) frames depression assessment through Drawing Projection Test (DPT) data such as PPAT sketches, converting visual stroke and layout patterns into psychological semantic captions via tailored LLM prompts [?]. The system fuses visual-perception and semantic generation modules to output a depression vs. non-depression classification, and shows a 17.6 % performance gain compared to traditional psychologist assessments. Unlike methods based on language or sentiment, VS-LLM highlights how multimodal sketch-to-semantics translation can enrich psychological evaluation.

Comprehensive mental health support is explored through Mental-LLM, which evaluates and instruction-tunes large language models for multi-task mental health prediction using online textual data rather than therapeutic intervention [49]. Advancing assessment capabilities, ProMind-LLM extends this direction by integrating subjective mental records with objective behavioral sensor data, leveraging domain-specific pretraining and causal chain-of-thought reasoning to enable more robust mental health risk assessment [107].

3.5.5 Anxiety and Trauma-Related Disorders

Anxiety and trauma disorders demand differentiated methods of approach with a consideration of the intricate interplay of psychological symptoms, physical responses, and behavioral presentations. Scalable AI frameworks emphasize early identification with behavior indicators, extensive risk profiling, and adaptive systems of therapeutic support with changing presentations of symptoms.

TRauma UNderstanding and STructured Assessments (TRUST) introduces an LLM-based diagnostic dialogue system that conducts formal structured PTSD interviews aligned with DSM-5 CAPS-5 criteria, enabling automated clinical assessment rather than therapeutic intervention [110]. Complementing this assessment focus, recent work on automatic PTSD diagnosis leverages LLM-generated text augmentation from clinical transcripts to address data imbalance and improve classification performance, demonstrating the role of LLMs in enhancing diagnostic robustness in low-resource trauma settings [135].

3.5.6 Neurodevelopmental Disorders

Neurodevelopmental disorders such as autism and ADHD are best addressed when they are detected early and treated with approaches tailored to each child's unique developmental path. Large-scale AI models are now helping by analyzing patterns in behavior, assessing social interactions, and creating adaptive support systems that grow and adjust as children's needs change over time.

Comprehensive assessment approaches in neurodevelopmental disorders are demonstrated by Kulkarni et al., who leverage LLMs to analyze video-based behavioral signals for early ADHD detection, using multimodal behavioral pattern recognition to support objective screening rather than downstream intervention [136]. Assessment of autistic social reciprocity is further advanced by SocialRecNet, which

utilizes multimodal alignment of speech and text with LLM-based reasoning to estimate autism diagnostic observation schedule social reciprocity scores for diagnostic support [109].

Specialized communication support is provided through ASD-Chat, which offers an LLM-driven intervention system grounded in verbal behavior milestones assessment and placement program, incorporating structured conversational paradigms, individualized preference adaptation, and clinically aligned turn-taking protocols to facilitate social communication skill development [94].

4 Public Data Cohorts for Computational Neuroscience

The rapid growth of computational neuroscience research has been aided by the existence of large, diverse, and high-quality public datasets from numerous neuroimaging modalities and clinical contexts. These data types encompass a wide range of techniques that include high-temporal-resolution electrophysiological recording with precision in the millisecond range, to high-spatial-resolution structural and functional neuroimaging data relevant for detailed anatomical and functional brain organization. The dataset scales are considerable, varying from in-depth studies of dozens of subjects to population-based studies with tens of thousands of subjects, for example, collectively amounting to terabytes of neural data for robust statistical analyses and generalizable computational models.

The clinical utility of these datasets reaches across the full spectrum of neurological and psychiatric disorders, including neurodegenerative diseases, stroke, epilepsy, autism spectrum disorders, and mental health disorders, while being a resource for basic research on cognitive neuroscience, brain-computer interfaces, and neural decoding. Notably, multimodal datasets have emerged to employ multiple recording techniques within the same subjects, promoting the complementary strengths of those modalities. Electrophysiological methods offer high temporal resolution, while neuroimaging methods offer strong spatial resolution. These extensive multimodal datasets, along with standardized data formats and open-access longitudinal datasets, have democratized neuroscience research and aided in the creation of innovative computational methods to better understand the brain and its functional impairment.

Table 5: Comprehensive Overview of Public Datasets for Computational Neuroscience Research

Dataset	Modality	Subjects	Data Size	Application Domain
EEG Datasets				
TUH EEG Corpus [137]	EEG	14,987+	1.7TB / 21,787h	General EEG analysis
TUAB [138]	EEG	2,329	1,139h	Abnormality detection
TUAR [139]	EEG	213	83.7h	Artifact detection
TUSL [137]	EEG	38	27.5h	Slowing events classification
TUEV [137]	EEG	Various	–	Clinical evaluation
Siena Scalp EEG [140]	EEG	14	141h	Scalp EEG analysis
SEED-IV [141]	EEG	15	–	Emotion recognition
SEED-V [142]	EEG	15	32.7h	Emotion recognition
DEAP [143]	EEG	32	–	Emotion recognition
FACED [144]	EEG	Various	–	Facial emotion analysis
CHB-MIT [145]	EEG	Pediatric	–	Pediatric epilepsy
MIBCI [146]	EEG	Various	–	Motor imagery BCI
BCIC4-1 [147]	EEG	7	–	Motor imagery BCI
Sleep-EDF [148]	EEG	Various	–	Sleep staging
EEGMat [149]	EEG	Various	–	Material recognition
STEW [150]	EEG	Various	–	Specialized tasks
Go-Nogo [151]	EEG	14	–	Visual categorization
MusicEEG [152]	EEG	31	–	Temporal dynamics
HBN EO/EC [153]	EEG	2,952	–	Resting state (pediatric)
HBN-EEG [153]	EEG	1,897	–	Multiple tasks (pediatric)
Features-EEG [154]	EEG	16	–	Visual feature processing
HFO [155]	EEG	30	–	Pediatric epilepsy
PEARL-Neuro [156]	EEG	79	–	Cognitive tasks
RestCog [157]	EEG	60	–	Resting state cognition
Awakening [158]	EEG	21	–	Sedation studies
AD-Auditory [159]	EEG	Various	–	Alzheimer's auditory
ADFSU [160]	EEG	Various	–	Alzheimer's studies
ADFTD [161]	EEG	Various	–	Frontotemporal dementia
ADSZ [162] [163]	EEG	Various	–	Alzheimer's seizure
APAVA [164] [165]	EEG	Various	–	Aphasia assessment
BrainLat [166]	EEG	Various	–	Latin brain studies
Cognision-ERP [167]	EEG	Various	–	Event-related potentials
Cognision-rsEEG [168]	EEG	Various	–	Resting state EEG
CNBPM [169]	EEG	Various	–	Brain pathology
MEG Datasets				
MEG-MASC [170]	MEG	27	2h/subject	Naturalistic stories
MEG-Narrative [171]	MEG	3	10h/subject	Naturalistic stories
OMEGA [172]	MEG	644	–	Resting state + pathology
CC700 [173]	MEG	700	–	Multiple cognitive tasks
AversiveMEG [174]	MEG	28	–	Aversive learning
MIND [175]	MEG	8	–	Somatosensory stimulation
SMN4Lang [176]	MEG	12	6h/subject	Language comprehension
THINGS-MEG [177]	MEG	4	–	Object recognition
ASWR-MEG [178]	MEG	24	–	Word sequence processing
ImageLine [179]	MEG	30	–	Visual object processing
NeuroMorph [180]	MEG	24	–	Lexical decision tasks
Kymata-SOTO [181]	MEG/EEG	35	–	Multi-language conversations
MRI Datasets				
HCP [182]	MRI/MEG	700+	–	Multi-modal brain imaging
UK Biobank [183]	MRI/fMRI	61,038+	82,800 images	Population neuroimaging

Dataset	Modality	Subjects	Data Size	Application Domain
ADNI [184]	MRI/PET	Various	–	Alzheimer's disease
OASIS-2 [185]	MRI	Various	–	Cross-sectional aging
OASIS-3 [186]	MRI	Various	–	Longitudinal aging
BraTS-2015 [187]	MRI	Various	–	Brain tumor segmentation
BraTS-2019 [188]	MRI	Various	–	Brain tumor segmentation
BraTS-2021 [189]	MRI	Various	5,004+ images	Brain tumor segmentation
ATLAS [190]	MRI	Various	655 images	Stroke lesion analysis
ABIDE I [191]	MRI	Various	–	Autism spectrum disorder
ABIDE II [192]	MRI	Various	–	Autism spectrum disorder
PPMI [193]	MRI/DaTscan	Various	–	Parkinson's disease
MCSA [194]	MRI	Various	–	Cognitive aging
SOOP [195]	MRI	Various	–	Brain development
CBTN LGG [196]	MRI	Various	–	Pediatric brain tumors
MIRIAD [197]	MRI	Various	–	Dementia research
DLBS [198]	MRI	Various	–	Brain development
UCSF-PDGM [199]	MRI	Various	–	Pediatric brain tumors
QIN-GBM [200]	MRI	Various	–	Glioblastoma research
UPENN-GBM [201]	MRI	Various	–	Glioblastoma research
DFCI/BCH LGG [77]	MRI	Various	–	Low-grade glioma
DFCI/BCH HGG [77]	MRI	Various	–	High-grade glioma
RIDER [202]	MRI	Various	–	Imaging biomarkers
wu1200 [182]	MRI	Various	–	Institutional dataset
LONG579 [203]	MRI	Various	–	Longitudinal studies
BABY [204]	MRI	Various	–	Infant brain development
AOMIC [205]	MRI	Various	–	Open MRI collection
Calgary [206]	MRI	Various	–	Canadian brain imaging
HaN [207]	MRI	Various	–	Healthy aging
NIMH [208]	MRI	Various	–	Mental health research
ICBM [209]	MRI	Various	–	Brain mapping consortium
IXI [210]	MRI	Various	–	Information extraction
PING [211]	MRI	Various	–	Pediatric imaging
Pixar [212]	MRI	Various	–	Specialized collection
SALD [213]	MRI	Various	–	Aging and dementia
RadArt [214]	MRI	Various	–	Radiological artifacts
Rhineland Study [215]	MRI	Various	–	Population study
SchizConnect [216]	MRI	Various	–	Schizophrenia research
OpenBHB [217]	MRI	Various	–	Open brain imaging
MSSEG [218]	MRI	Various	–	Multiple sclerosis
ISLES2022 [219]	MRI	Various	–	Stroke lesion segmentation
WMH2017 [220]	MRI	Various	–	White matter hyperintensities
MSLesSeg [221]	MRI	75	115	Multiple Sclerosis Lesion Segmentation
Visual Datasets				
Natural Scenes [222]	fMRI	8	–	Visual scene processing
BOLD5000 [223]	fMRI	Various	136,000 segments/340h	Visual object recognition
GOD [224]	fMRI	Various	–	Object recognition
MS-COCO [225]	Images	–	–	Object recognition (stimuli)
Flick30k [226]	Images	–	–	Image-caption pairs
ConceptualCaptions12M [227]	Multi-modal	–	–	Vision-text
ConceptualCaptions3M [228]	Multi-modal	–	–	Vision-text
SBU [229]	Multi-modal	–	–	Vision-text
VG [230]	Multi-modal	–	–	Vision-text
Visual stimuli [231]	fMRI	594	53 time-steps	Object recognition
Clinical and Disease-Specific Datasets				
PETfrog [232]	PET	Various	–	PET imaging
ADReSSo [233]	Audio/Clinical	Various	–	Alzheimer's speech analysis
NCCT [234]	CT	Various	–	Neuroimaging
Dreaddit [235]	Text	Various	–	Depression detection
CSSRS-Suicide [236]	Clinical	Various	–	Suicide risk assessment
PPAT [51]	Various	Various	–	Neuropsychological assessment
DepSeverity [237]	Clinical	Various	–	Depression severity
SDCNL [238]	Clinical	Various	–	Depression analysis
PMData [239]	Clinical	Various	–	Mental health data
Globem [240]	Clinical	Various	–	Global mental health
E-DAIC [241]	Audio/Clinical	Various	–	Depression interview
ADOS [242]	Clinical	Various	–	Autism diagnostic
CQ500 [243]	CT	500	491	head trauma or stroke analysis
Psych-101 [244]	Psychological	Various	–	Psychology dataset
ClinicalQA [112]	Clinical	Various	–	Clinical Q&A
Multimodal MCI [245]	Cognitive	Various	–	Cognitive assessment
Specialized Research Datasets				
POYO-DANDI [246]	Neural spikes	9 primates	78 sessions	Motor/somatosensory cortex
Knowledge, Literature Resources and Other Databases				
PubMed	Literature	–	Abstracts	Neuroscience literature
Wikipedia	Encyclopedia	–	–	General knowledge
NeuroLex [247]	Knowledge	–	–	Neuroscience ontology
NeuroMorpho [248]	Morphology	–	–	Neuronal morphology
OpenNeuro [249]	Multi-modal neuroimaging data	–	–	Comprehensive neuroimaging research
Neurosurgical Atlas [250]	Literature	–	–	Neurosurgical atlas
NLI4CT [251]	Clinical text	–	–	Clinical trial inference
Merck Manual [252]	Medical	–	–	Medical reference
Neurology textbooks	Literature	–	–	Educational resources

We have compiled major datasets from the neuroscience literature over the past two decades, as shown in Table 5. These public datasets vary widely in scope and scale, and have significantly advanced computational neuroscience research by providing access to high-quality neural data across different recording methods, subject populations, and experimental designs.

5   Future Development and Challenges

Large-scale AI models are increasingly adopted in neuroscience research and clinical practice due to their exceptional capabilities in pattern recognition and data analysis. However, their implementation faces substantial technical and methodological challenges that currently limit their broader adoption.

5.1 Generalization, Multimodal Integration, and Model Scalability

Arguably, the biggest challenge lies with obtaining good generalization across a wide variety of studies and patient populations while being computationally efficient. The underlying challenge lies with the intrinsic variability of the neural data from populations, age spans, and pathological conditions, and thus requires sophisticated domain adaptation techniques that are able to retain performance while permitting biological variability [34, 53]. This discrepancy largely explains why current approaches demonstrate strong performance in controlled laboratory experiments but often fail to generalize to real-world clinical environments characterized by variable data quality, heterogeneous acquisition protocols, and diverse patient populations.

The issue of generalization becomes further complicated with the advent of multimodal data. Incorporation of these data involves innovations of temporal and spatial alignment at varying scales of measurement that cannot efficiently be handled with data concatenation. It entails both technical issues of cross-modal representation learning and theory issues of how varying neural modalities of measurement correspond with underlying brain function [91, 92]. A critical challenge is preserving the unique information content of each modality while enabling integrative fusion that enhances rather than compromises predictive performance.

Both the generalization and the multimodal integration challenges are further complicated by computational scalability limitations. With greater computational needs for training sophisticated models come limitations that could cause research capacities to concentrate in well-funded institutions, inhibiting research diversity and practicality [8, 16]. Overcoming this necessitates architecture innovations where efficiency takes priority alongside performance, creating methods that may broaden accessibility and usability while still maintaining performance. Both algorithmic advances and dedicated hardware architecture designs optimized for neuroscience workloads are involved.

5.2 Clinical Translation and Interpretability

From research to practice, translation entails managing interpretability at a wide variety of levels, spanning individual-level predictions through to the macro-level characterization of system-wide behavior. It entails beyond model-level decision explanation and reaching AI systems that can reason clinically and align with current medical knowledge and practice guidelines [36, 90]. It also requires building a transparent architecture intrinsically and not with post-hoc techniques of explanation that cannot always accurately represent model behavior in practice. Explainable Artificial Intelligence (XAI) refers to AI systems designed to make their decision-making processes transparent, interpretable, and understandable to humans [253]. Goal-driven explainability processes in healthcare focus on enabling AI systems, particularly AI agents and autonomous decision-makers, to generate justifications for their actions based on explicit goals, intentions, beliefs, or plans [254]. Unlike purely data-driven methods that are often used in a post-hoc manner, goal-driven approaches, aided by the natural language generation capacity of LLMs, allow such systems to provide context-sensitive, human-like rationales for their reasoning, plans, and actions. This form of explanation aligns with clinical reasoning patterns and facilitates human-AI collaboration in decision-making and is thus a major focus of healthcare AI systems moving forward [255].

Apart from interpretability, clinical trust also involves technical correctness as well as the proper human-AI collaboration at health clinics. Creating successful clinical AI systems entails learning how clinicians incorporate AI feedback into their judgments, conveying uncertainty, and ensuring proper human supervision while employing AI abilities [40, 103]. AI systems also need to integrate within clinical workflows by supplying relevant and timely information supporting current practices and not disturbing current practices. Establishing clinical trust also relies on robust regulatory frameworks. Regulatory challenges in neuroscience AI arise from the complexity of brain-based applications, where incorrect decisions carry high stakes and model mechanisms are often poorly understood. Developing appropriate regulatory frameworks requires balancing innovation with patient safety while addressing the unique characteristics of brain data and neurological conditions [35, 77]. Regulatory frameworks should balance rapid AI advancement with safety standards through clear validation guidelines, appropriate outcome measures, and continuous model monitoring. Successful implementation requires training healthcare professionals, building deployment infrastructure, and creating interdisciplinary teams to bridge technical and clinical expertise.

5.3 Data Governance and Ethical Principles

Large-scale neural modeling also has similar problems of fundamental data quality and standardization, and ethical issues that are intimately tied together. Standardization of neural data acquisition, preprocessing, and annotation remains inconsistent across research groups and clinical sites, posing a significant bottleneck to the development of truly generalizable models. Although techniques like BrainGFM's multi-atlas training demonstrate promising results of standardized data aggregation, establishing full data quality frameworks requires much repeated effort [45]. These data quality and standardization issues are further complicated in the neuroscience example with problems of privacy and security.

These privacy issues are especially heightened as brain data discloses sensitive information regarding individuals' mental status, cognitive capacities, and neurological status. Overcoming these issues involves giving high priority to privacy-preserving methods like differential privacy, federated learning, and secure multiparty computation in order to allow for extensive model training at a large scale while maintaining patient confidentiality. For instance, federated learning methods hold special promise through the use of distributed datasets while at the same time ensuring data privacy and institutional autonomy with a single solution tackling both issues of standardization and privacy [95]. Patient consent and privacy are of critical importance, particularly for genomic data, which carries the risk of re-identification [256]. The sharing of these data may be prohibited by ethics frameworks and data-sharing laws. A federated learning approach, whereby raw training data remains distributed across individual institutions, is one solution [257]. Participating sites train a common model using their data, and the encrypted outputs are transmitted to a common server for aggregation, and the outputs of the aggregated analysis are returned to each participating site. In addition, the creation of robust ethical guidelines specifically crafted with neuroscience AI applications will also become critical for ensuring public confidence and accountable innovation. These guidelines should incorporate issues of algorithmic bias, AI-assisted diagnosis, informed consent, and adequate utilization of synthetic neural data generation abilities. Importantly, such models should neither intensify current disparities in healthcare nor become exclusive and non-representative of global populations. Owing to the aforementioned issues, international standards of neuroscience AI creation demand international collaboration among researchers, clinicians, ethicists, and regulatory committees [258].

5.4 Emerging Frontiers and Future Opportunities

The intersection of neural recording technologies' advancements with computational techniques and AI systems opens up new avenues of examining brain function and neuro disease treatment. Real-time adaptive BCI driven by such models holds promise as a treatment option for paralysis, depression, and other neurodisorders [3]. Brain-inspired AI systems drawing from biological neural principles may further improve computational efficacy and model understandability [259], while neuroscience research-related LLMs offer new frameworks for explaining language processing and cognitive mechanisms [52]. Synthetic advances in generating neural data resolve core research challenges, especially data availability in rare neurological disorders and privacy restrictions in clinical datasets [3, 260]. These synthetic datasets allow for rigorous model testing across heterogeneous populations and facilitate hypothesis-driven research in formerly data-constrained areas. The data augmentation capacities are crucial towards establishing generalizable models able to function correctly across a variety of patient populations and clinical scenarios. Realization of opportunities, though, requires collaborative ecosystems beyond boundaries of classical disciplines [26]. International collaborative mechanisms of neuroscientists, computer scientists, clinicians, and industrial collaborators are driving transformative research of brain sciences and AI and creating innovative methods and ethical data-sharing practices towards greater understanding of neural processes [261]. These collaborators specify global data-sharing frameworks to get beyond privacy and ethical challenges while facilitating coordination of large-scale research at a global level [262]. Specialized training programs are simultaneously cultivating researchers proficient in both neuroscience and AI methodologies, thereby building the human capital necessary to advance the field [263].

6   Conclusion

The development of large-scale AI models in neuroscience is gradually expanding our ability to characterize brain function and support clinical decision-making. This survey has reviewed the diverse range of such models, from neural signal processing architectures used for decoding neural activity to clinical decision support systems that incorporate multimodal biomedical information. These developments indicate that large-scale AI models are beginning to be used not only as analytical tools but also as practical components within research workflows and early-stage translational settings. The progress summarized here reflects a gradual shift from isolated proof-of-concept demonstrations toward more systematic applications with measurable relevance to both foundational and applied neuroscience.

At the same time, several challenges remain unresolved, including robustness across heterogeneous populations, interpretability in realistic clinical contexts, and the ethical and regulatory considerations associated with responsible deployment. Progress in these areas will require sustained collaboration across neuroscience, computer science, clinical medicine, and regulatory policy. While large-scale AI models hold meaningful potential to support both research and clinical practice, their long-term impact will depend on steady improvements in technical reliability, dataset governance, and translational oversight. Ongoing work in these directions provides a foundation for further progress without presupposing that current advances will directly translate into widespread clinical integration.

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