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Emergence of Artificial Intelligence in Multiple Domains of Neurology: A Review

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Abstract: Artificial Intelligence (AI) has emerged as a transformative force across multiple domains of neurology, reshaping traditional paradigms in diagnosis, therapeutics, research, and patient care. This review explores the breadth and depth of AI applications within neurological sciences, emphasizing clinical innovations, translational potential, and ethical implications. In diagnostics, AI has significantly enhanced neuroimaging interpretation, disease classification, and multimodal data integration—enabling earlier and more accurate detection of conditions such as Alzheimer's disease, stroke, and Parkinson's disease. Therapeutically, AI-driven adaptive deep brain stimulation (aDBS) and closed-loop neuromodulation systems are setting new standards for personalized treatment, offering dynamic feedback-based modulation of neural activity. The review also addresses AI's critical role in drug discovery and development, where deep learning and generative models have accelerated target identification, virtual screening, and molecule generation. Assistive technologies, particularly brain–computer interfaces (BCIs), have advanced rapidly, enabling communication and mobility for individuals with profound neurological disabilities. These innovations include speech prostheses, silent-speech decoding, and robotic sensory feedback systems. Despite these advancements, the integration of AI in neurology faces challenges including data bias, explainability, and privacy concerns. The future of AI-driven neurology will depend on interdisciplinary collaboration, ethical governance, and the continued development of interpretable, equitable, and human-centered technologies. This review synthesizes current progress while mapping trajectories for future research and clinical implementation.

INTRODUCTION

Artificial Intelligence (AI)—once a futuristic concept—has rapidly permeated modern medicine, offering unprecedented tools for diagnosis, monitoring, and treatment across clinical disciplines (Topol, 2019; Kelly et al., 2019). Artificial Intelligence (AI) in medicine primarily relies on Machine Learning (ML) and its subset Deep Learning (DL), which deviate from rule-based systems by identifying patterns in data (Mitchell, 1997; LeCun et al., 2015). Since its origin in the 1950s, ML has evolved to include DL techniques like transformers, which power generative AI tools such as ChatGPT® (McCarthy et al., 1955; Vaswani et al., 2017; OpenAI, 2023). These models enable sophisticated applications in neurology by accelerating data analysis, enhancing diagnostic accuracy, and tailoring treatment based on patient-specific data (Bösel et al., 2025; Litjens et al., 2017). Despite their strengths in specialized tasks, such systems still fall short in holistic reasoning akin to human experts (Rudin, 2019). AI's integration allows for real-time processing of vast medical records, facilitating earlier and more accurate interventions (Topol, 2019).

ML approaches can be classified based on the learning method—supervised, unsupervised, semi-supervised, and reinforcement learning—and whether they are traditional or DL models (Russell & Norvig, 2021). Traditional ML requires manual selection of features, whereas DL autonomously extracts complex features through neural networks (LeCun et al., 2015; Goodfellow et al., 2016). Transformers, a recent DL innovation, use self-attention mechanisms to process long and context-rich text effectively, making them highly suitable for tasks like translation and text generation (Vaswani et al., 2017). This architecture is now extending into image and video generation, often in combination with diffusion models, pushing the frontiers of generative AI across diverse data types (Ramesh et al., 2022; Ho et al., 2020).

Neurology, despite its inherent complexity, is no exception. From neuroimaging to real-time clinical decision support, AI continues to revolutionize both scientific understanding and patient care in neurological diseases (Bösel et al., 2025; Vieira et al., 2017). In neurology, AI is being rapidly integrated into domains such as stroke diagnosis, epilepsy prediction, neurocritical care, and brain injury assessment (Titano et al., 2018; Orrù et al., 2012). Recent narrative and scoping reviews emphasize how AI, particularly machine learning and deep neural networks, is advancing applications in areas such as stroke, epilepsy, traumatic brain injury, and intensive neurocritical care (Bösel et al., 2025; Kelly et al., 2019). Moreover, AI is increasingly incorporated into neurology education and training—spurring dialogue around curriculum innovation, clinical workflows, and physician awareness (Bösel et al., 2025).

This review aims to synthesize these developments, analyzing AI’s roles in diagnostics, therapeutics, research integration, and assistive technologies. Alongside the promises, we also critically address ethical challenges, data biases, algorithmic opacity, and equity (Rudin, 2019; Kelly et al., 2019). Finally, we highlight emerging frameworks—such as digital twins and AI-driven evidence synthesis—that could shape the future of neurology (Björnsson et al., 2020).

DIAGNOSTIC APPLICATIONS OF AI IN NEUROLOGY

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has revolutionized the diagnostic landscape in neurology by augmenting both accuracy and efficiency (LeCun et al., 2015; Litjens et al., 2017; Topol, 2019). Initially focused on neuroimaging analysis, AI’s diagnostic utility now spans diverse modalities—from imaging to electrophysiology and consciousness disorders (Esteva et al., 2017; Rajpurkar et al., 2017; Bösel et al., 2025).

Applying Machine Learning (ML) and Deep Learning (DL) to medicine, especially neurology, reveals a major challenge known as the "black box" problem, where the internal logic of complex models like neural networks remains opaque (Rudin, 2019). While simpler models are interpretable, newer AI methods often lack transparency, prompting a push for "explainable AI" to make decision-making processes more understandable (Doshi-Velez & Kim, 2017). Neurology’s diverse data sources—ranging from clinical notes to imaging and physiological data—require robust AI infrastructures (Topol, 2019). Hospitals aiming to integrate AI must establish systems for data collection, storage, and ethical usage (European Commission, 2019). Developing clinically validated AI tools involves multiple stages, including external and prospective validation using data from varied institutions (Kelly et al., 2019).

Effective AI integration in neurology depends on interdisciplinary collaboration (Bösel et al., 2025). Clinicians contribute vital domain knowledge for accurate data labeling and help interpret model outputs to ensure clinical relevance (Topol, 2019). Data engineers build and maintain the technical infrastructure, while data scientists design, train, and evaluate models (Russell & Norvig, 2021). Ensuring a model's efficacy through clinical trials is crucial, as models trained on single-center data may lack generalizability (Kelly et al., 2019). Federated and transfer learning, along with privacy-preserving methods like homomorphic encryption, allow cross-institutional collaboration without compromising patient confidentiality, improving model fairness and performance (Rieke et al., 2020; Li et al., 2020).

Neuroimaging and Early Detection

Deep learning models, such as convolutional neural networks and adversarial neural networks, have demonstrated robust performance in segmenting brain structures and detecting neurological pathologies in MRI, fMRI, and PET scans (e.g., Alzheimer's, Parkinson's, multiple sclerosis) (Litjens et al., 2017; Vieira et al., 2017; Yang et al., 2018). Techniques like adversarial networks improve robustness in semantic segmentation, enhancing identification of subtle markers and reducing subjectivity (Yang et al., 2018). Several reviews emphasize these approaches' potential for early diagnosis of neurological and psychiatric disorders, while also highlighting the need for interpretability and clinical validation (Vieira et al., 2017; Kelly et al., 2019).

Multimodal Data Integration and ML Approaches

Beyond imaging, ML has been applied to integrate various data types—such as electrophysiological signals and biomarkers—to improve disease risk stratification and early intervention (Orrù et al., 2012). For example, algorithms trained on multimodal datasets (imaging, genetics, clinical history) have shown predictive utility in conditions like Alzheimer's and Parkinson's disease (Zhang et al., 2011; Latourelle et al., 2017).

Disorders of Consciousness and Emergent Neurological Conditions

AI's diagnostic potential extends into critically important and time-sensitive areas such as disorders of consciousness (DOC). A systematic review demonstrated AI's ability to enhance diagnosis in DOC, offering more rapid and objective assessments (Comanducci et al., 2020). This role is particularly notable in emergency neurology—where rapid AI-based triage or decision support can be lifesaving (Titano et al., 2018; Bösel et al., 2025).

Despite its potential, implementing AI in healthcare faces several hurdles: high financial costs, the need for skilled personnel, and stringent data privacy and regulatory requirements (Kelly et al., 2019). Institutions must comply with frameworks like HIPAA or GDPR while safeguarding against cyber threats (European Parliament & Council of the European Union, 2016). Establishing ethical governance is essential to mitigate algorithmic bias and misuse (Rudin, 2019). Key regulatory bodies such as the FDA and EMA oversee these implementations to ensure safety, fairness, and patient trust in AI-driven care (U.S. Food and Drug Administration [FDA], 2021; European Medicines Agency [EMA], 2020).

THERAPEUTIC AND NEUROMODULATORY INNOVATIONS

One of the most transformative areas of AI in neurology lies in therapeutic applications, notably in neuromodulation and adaptive treatments (Bösel et al., 2025; Little et al., 2013).

Adaptive Deep Brain Stimulation (aDBS)

Adaptive Deep Brain Stimulation (aDBS) represents a landmark in AI-driven neuromodulation. Unlike conventional DBS—which delivers constant electrical stimulation—aDBS systems dynamically adjust stimulation intensity in response to real-time neural biomarkers or oscillations (Little et al., 2013; Rosa et al., 2017). Preliminary studies have shown substantial improvements in motor symptoms, fewer side effects, and reduced energy consumption (Little et al., 2013; Rosa et al., 2017).

In 2025, the FDA approved the first aDBS system following results from the ADAPT PD trial, which demonstrated high patient retention and a favorable safety profile (U.S. Food and Drug Administration [FDA], 2025). Additionally, emerging evidence points toward aDBS's potential to manage non-motor symptoms, such as anxiety in Parkinson's disease, by targeting specific neural oscillations (Neumann et al., 2018).

Automated Programming and Closed-Loop DBS Systems

AI is also streamlining DBS parameter optimization. Research has explored automated DBS programming, leveraging Parkinson's disease biomarkers to identify optimal stimulation configurations, thereby enhancing both efficiency and outcome consistency (Houston et al., 2019; Haddock et al., 2022).

Notably, in early 2025, Medtronic achieved CE marking for a closed-loop DBS system—Alpha DBS—which monitors brain signals and adapts stimulation thresholds autonomously (Medtronic, 2025). Clinical studies indicate these systems can maintain efficacy while delivering lower electrical energy and reducing symptom severity (Little et al., 2013; Rosa et al., 2017).

Extending DBS Beyond Movement Disorders

AI-enhanced DBS is making inroads beyond movement disorders. Research has shown promising cognitive and consciousness recovery in patients with disorders of consciousness by targeting the central thalamus (Schiff et al., 2007; Corazzol et al., 2017). In psychiatry, DBS has helped alleviate severe depression and obsessive–compulsive disorder (OCD), although outcomes remain variable and further validation is needed (Holtzheimer et al., 2017; Denys et al., 2010). Additionally, pioneering work involves DBS targeting the nucleus accumbens to reduce drug cravings in opioid addiction—an early, investigational but intriguing direction (Kuhn et al., 2014).

Other non-invasive modalities like transcranial focused ultrasound (tFUS), offering deep, millimetric precision, are also under investigation for AI-controlled neuromodulation—though clinical studies remain limited (Fomenko et al., 2018).

AI IN NEUROSCIENCE RESEARCH & DRUG DISCOVERY

The integration of artificial intelligence (AI) into neuroscience and drug discovery has revolutionized the landscape, enabling accelerated identification of therapeutic targets, de novo compound design, personalized treatment strategies, and more efficient clinical trial models (Schneider et al., 2020; Vamathevan et al., 2019).

Target Identification and Multi-Omics Integration

AI-driven approaches facilitate the analysis of complex, high-dimensional data—such as genomics, proteomics, neuroimaging, and clinical records—enabling more precise identification of molecular targets and disease signatures (Fang et al., 2022; Zitnik et al., 2019). Neural networks trained on multimodal datasets have demonstrated efficacy in elucidating pathophysiological pathways, especially in brain diseases (Fang et al., 2022). Network analysis techniques, including tools like WGCNA and STRING, combined with bioinformatics pipelines, have enhanced our understanding of neurodegenerative processes and exposed new therapeutic avenues (Langfelder & Horvath, 2008; Szklarczyk et al., 2023).

Structure Prediction and Virtual Screening

Deep learning models such as AlphaFold—and its later iteration, AlphaFold 3—have dramatically advanced the accuracy of protein structure prediction, including interactions with nucleic acids, ligands, or drug molecules (Jumper et al., 2021; Abramson et al., 2024). These capabilities streamline structure-based drug design, facilitating both precise docking campaigns and target-druggability assessments (Schneider et al., 2020). Furthermore, ultra-large-scale docking approaches enable rapid virtual screening across massive chemical libraries, accelerating the discovery of novel scaffolds for pharmacological intervention (Lyu et al., 2019).

Generative Design: De Novo Molecule Generation and Graph Neural Networks

AI supports generative de novo molecule design workflows capable of producing innovative chemical structures with predefined biological and pharmacokinetic properties (Zhavoronkov et al., 2019; Wang et al., 2021). Techniques such as Retro Drug Design (RDD), which employ deep learning and molecular descriptors to propose novel candidates, have yielded biologically active compounds in early drug discovery stages (Wang et al., 2021). Graph Neural Networks (GNNs), an especially promising paradigm, model molecules as graphs and facilitate property prediction, virtual screening, molecular generation, and synthesis planning with enhanced interpretability and scalability (Duvenaud et al., 2015; Zhang et al., 2023).

Specialized AI Models and Novel Approaches

Recent innovations such as graph-based neural models for perturbation prediction have enabled identification of gene targets whose manipulation could reverse diseased cellular states, streamlining therapeutic target prioritization (Zitnik et al., 2019). In neurological applications, these approaches have been used to uncover candidate interventions for Alzheimer’s and Parkinson’s diseases (Fang et al., 2022).

AI-Enabled Drug Development Ecosystems and Platforms

Several AI-powered platforms and institutions are pioneering neurotherapeutic discoveries:

- **Eli Lilly (TuneLab initiative):** Expanding AI-powered drug discovery infrastructure to external biotech partners (Vamathevan et al., 2019).
- **Isomorphic Labs (Alphabet/DeepMind):** Leveraging AlphaFold-based structural biology and AI pipelines for therapeutic development (Jumper et al., 2021; Abramson et al., 2024).
- **Insilico Medicine:** Demonstrated AI-designed drug candidates entering clinical evaluation (Zhavoronkov et al., 2019).
- **Owkin:** Applies federated learning to preserve patient privacy while improving predictive performance in distributed datasets (Rieke et al., 2020).
- **MIT Jameel Clinic:** Advancing AI-driven antibiotic and therapeutic discovery using deep learning frameworks (Stokes et al., 2020).

AI in Early Clinical Development and Trial Optimization

AI is increasingly integrated into early-phase drug development—optimizing patient recruitment, predicting therapeutic responses, and designing efficient adaptive clinical trials (Vamathevan et al., 2019; Ocaña et al., 2023).

Techniques such as synthetic control arms and digital twins simulate trial outcomes using real-world or virtual patient data, reducing costs, timelines, and ethical burdens (Ocaña et al., 2023).

Challenges and Ethical Considerations

Despite its promise, AI-driven drug discovery faces several obstacles:

- **Data Quality and Bias:** Limited or non-representative datasets can compromise generalizability, leading to overfitting or invalid predictions (Blanco-González et al., 2023; Ocaña et al., 2023).
- **Explainability and Regulatory Alignment:** Transparent model behavior and rigorous validation are essential for clinical adoption (Blanco-González et al., 2023; Rudin, 2019).
- **Ethical and Privacy Concerns:** Federated learning provides partial mitigation, yet challenges remain regarding consent, governance, and bias (Rieke et al., 2020).

ASSISTIVE TECHNOLOGIES AND INTERFACES

Advances in artificial intelligence (AI) are dramatically reshaping assistive technologies in neurology, particularly through brain–computer interfaces (BCIs) and innovative silent-speech communication systems (Wolpaw et al., 2002; Chaudhary et al., 2016).

Brain-Computer Interfaces (BCIs) in Assistive Care

BCIs enable direct communication between neural systems and external devices, providing unprecedented support for individuals with severe motor or speech impairments (Wolpaw et al., 2002; Lebedev & Nicolelis, 2006). Bibliometric analyses indicate a marked global increase in AI-enhanced BCI research, particularly in neurophysiological signal processing and assistive robotics (Chaudhary et al., 2016).

Clinically, BCIs allow patients with conditions such as amyotrophic lateral sclerosis (ALS) and paralysis to control computers, spell text, and operate smart devices using neural signals alone (Birbaumer et al., 1999; Pandarinath et al., 2017). State-of-the-art decoding algorithms—including multimodal fusion, sequential modeling, and transformer-based neural architectures—are advancing performance across visual, speech, and affective domains (Vaswani et al., 2017; Wang et al., 2022).

Notable commercial and translational implementations include:

- **Stentrode:** A minimally invasive endovascular BCI enabling wireless neural control without open-brain surgery (Oxley et al., 2016).
- **Precision Neuroscience cortical arrays:** High-resolution minimally invasive cortical recording systems supporting neural decoding research (Musk et al., 2019).
- **IntendiX:** A non-invasive EEG-based BCI using P300/SSVEP paradigms for communication and assistive control (Guger et al., 2009).
- **OpenBCI:** An open-source EEG/EMG hardware ecosystem supporting research and assistive innovation (Frey, 2016).

Beyond Thought: Enhancing Sensory Feedback and Speech Recovery

AI-enhanced BCIs are extending beyond motor control to restore sensory feedback and naturalistic communication:

- Real-time speech neuroprostheses have enabled stroke or ALS patients to translate neural activity into synthesized speech (Moses et al., 2021; Willett et al., 2023).
- Bidirectional BCIs incorporating somatosensory feedback have allowed paralyzed individuals to control robotic limbs while experiencing tactile sensations (Flesher et al., 2016).
- Internal speech decoding systems have demonstrated the feasibility of decoding imagined or attempted speech with substantial accuracy, while emphasizing safeguards for privacy (Makin et al., 2020).

Silent Speech Interfaces and Emerging AI Modalities

Emerging AI-driven interfaces extend assistive communication beyond traditional neural implants. Wearable silent-speech interfaces can decode subvocal articulatory signals captured from peripheral nerves and muscle activity, offering non-invasive communication pathways (Kapoor & Picard, 2018; Jorgensen et al., 2003).

FUTURE DIRECTIONS AND EMERGING FRONTIERS

Emerging trends indicate that AI, BCIs, and assistive technologies are poised to further transform neurology (Chaudhary et al., 2016).

Expanding BCI Ecosystems and Global Scaling

National strategies are increasingly prioritizing BCI development, including investments in scalable signal-decoding chips and neurotechnology infrastructure (OECD, 2019).

Toward Naturalistic, Multimodal Communication

Future BCIs are expected to integrate speech, motor, sensory, and cognitive domains into unified multimodal systems. Advances in GANs, transformers, and contrastive learning are enabling cross-modal decoding of EEG into speech, images, and text representations (Goodfellow et al., 2014; Vaswani et al., 2017).

Toward Predictive and Personalized Neurology

AI-driven predictive models are advancing personalized neurology, including digital twin frameworks and longitudinal disease modeling for Alzheimer's disease progression (Björnsson et al., 2020; Wang et al., 2021).

Robotics, Neuroprosthetics, and Cognitive Enhancement

The integration of AI with robotics and neuroprosthetics is improving rehabilitation outcomes and motor recovery (Hochberg et al., 2012). Combined AR/VR-assisted neurorehabilitation and adaptive prosthetic control represent promising frontiers (Laver et al., 2017).

Ensuring Ethical, Fair, and Equitable Innovation

Rapid advances in neural decoding raise important ethical concerns:

- Internal speech decoding necessitates privacy safeguards and consent frameworks (Ienca & Andorno, 2017).
- Global neurotechnology strategies must emphasize equitable access and collaborative governance (OECD, 2019).
- Trustworthy and interpretable AI systems are essential for regulatory and clinical acceptance (Rudin, 2019).

CONCLUSION

Artificial Intelligence (AI) ushers in a transformative era in neurology, reshaping how neurological conditions are diagnosed, understood, treated, and managed. From enhancing neuroimaging interpretation to pioneering adaptive deep brain stimulation and brain–

computer interfaces, AI is increasingly embedded in clinical and research workflows. Its capacity to analyze multimodal data, predict disease trajectories, and accelerate drug discovery is propelling neurology into an age of precision and personalization.

The integration of AI into diagnostic modalities has reduced subjectivity and improved early disease detection, particularly in disorders like Alzheimer's disease, stroke, and Parkinson's disease. In therapeutics, AI-fueled innovations—such as adaptive and closed-loop deep brain stimulation—demonstrate not only clinical efficacy but also pave the way for dynamic, patient-tailored neuromodulation. Moreover, AI's role in drug discovery—from target identification to virtual screening and molecule generation—has significantly condensed timelines, lowered costs, and revealed novel neurotherapeutic candidates.

Equally compelling are AI-enhanced assistive technologies, particularly BCIs, which are revolutionizing communication, mobility, and autonomy for patients with severe neurological disabilities. These systems—ranging from non-invasive EEG tools to implantable neural devices—are now capable of translating thought into speech, restoring sensory feedback, and even decoding internal monologues.

Nonetheless, these advances are accompanied by considerable challenges. Data bias, explainability, ethical transparency, and equitable access remain pivotal concerns. The potential to decode cognitive and affective states through neuro-AI raises profound ethical implications for privacy and autonomy. Addressing these challenges requires interdisciplinary collaboration among neurologists, data scientists, ethicists, and policymakers.

Looking ahead, the future of AI in neurology lies in its convergence with digital twins, robotics, AR/VR, and neuro-symbolic reasoning. Equally important is the integration of AI literacy into clinical education and regulatory frameworks. Only through responsible innovation, guided by clinical relevance and ethical foresight, can AI's full potential be realized—ushering in a future where neurology is not only smarter but also more human-centric.

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