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Research Article

EEG-Based Machine Learning in Pediatric Epilepsy Research: Worldwide Patterns, Recent Trends and Future Prospects: A Bibliometric Study

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ABSTRACT

Epilepsy is a common chronic neurological disease affecting approximately 65 million people worldwide, with almost 2 million incident cases each year. It is a disorder that has a different clinical appearance in children and a different diagnostic and therapeutic context due to immature neurodevelopment and the clinical and etiological variability of pediatric seizures. The most important is early and accurate diagnosis, as continued seizure activity is known to be associated with irreversible neuronal damage, cognitive deficits, and psychosocial complications. Notably, approximately 30% of pediatric cases are resistant to treatment with standard antiepileptic medications and surgery, highlighting the critical need for the development of novel diagnostic and prognostic tools. Although Electroencephalography (EEG) is still the foundation of the diagnosis and monitoring of epilepsy, traditional manual analysis is highly subjective, time consuming and prone to interrater variability. The advent of Machine Learning (ML) and Deep Learning (DL) architectures has revolutionized EEG analysis and has made it possible to achieve high-throughput, reproducible seizure detection and prediction for pooled sensitivities and specificities of >80% and a DL validation accuracy of 89-91%. This bibliometric review is systematic and uses keyword co-occurrence networks, temporal keyword evolution mapping, density visualizations and thematic clustering to analyze the literature from 2015-2025. Following an increase in numbers after 2014, publication output has now picked up considerably, with 261 publications and 6,124 citations in 2022. The seizure detection accuracy was shown to be 92-97% for the United States and China as the dominant contributors, and hybrid architectures with CNN attention provided the best results. For each research paper, the research field was identified via thematic analysis, which revealed three main clusters: seizure detection, signal processing, and multimodal neuroimaging integration. There remain key gaps, including in pediatric-specific datasets, model interpretation, and clinical translation, that require frameworks and structured interdisciplinary collaboration to ensure the responsible implementation of explainable AI. Further studies should focus on the design of explainable AI frameworks and collaborative cross-institutional validation for the development of personalized, data-driven pediatric epilepsy care.

Keywords: EEG, Machine Learning, Metanalysis, Pediatric Epilepsy.

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INTRODUCTION

Epilepsy is among the most prevalent long-term neurological conditions and is characterized by recurrent seizures resulting from abnormal electrical discharges in brain neurons. Each year, approximately 2 million new cases are diagnosed, impacting approximately 65 million individuals worldwide (Huang *et al*., 2025). Epilepsy in children and adolescents presents distinct diagnostic and therapeutic challenges because of the ongoing developmental changes in their brains and the varying types of seizures. The possible outcomes of epileptic seizures in this children include convulsions, temporary loss of consciousness, and various motor or sensory abnormalities (Verma *et al*., 2025). Children who experience frequent seizures may face serious consequences, including irreversible brain damage, cognitive impairments, behavioral challenges, and considerable emotional distress for their families. Approximately 30% of children with epilepsy continue to have drug-resistant epilepsy, highlighting the need for novel and useful methods not only for diagnosis but also for prognosis. Electroencephalography (EEG) is an important tool for both diagnosing and monitoring epilepsy. It records the electrical activity of the brain; any abnormal pattern indicates

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seizure activity (Huang *et al.*, 2025). This has been traditionally done EEG data recordings, which poses great challenges. In most cases, neurologists must go through a very tedious process that is subjective and prone to errors, especially in noisy conditions that represent typical clinical EEG recordings. This has led to the creation of improved automation. EEG analysis tools are intended to make diagnoses more accurate and faster. Pediatric epilepsy can be challenging to diagnose, particularly because of its variable and elusive symptoms, compounded further by the limitations of existing detection tools. Sophisticated models for analysis are therefore increasingly emphasized to support clinicians in detecting seizures at their onset and managing them appropriately. With better diagnostic accuracy, timely interventions would translate to reduced seizure frequency and intensity, hence resulting in better health outcomes over the long term for pediatric patients (Prasanna *et al.*, 2021). Electroencephalography (EEG), especially continuous EEG (cEEG), has become an indispensable tool in pediatric neurocritical care because of its ability to monitor real-time cerebral function. As the gold standard for seizure detection, cEEG may detect both clinical and subclinical seizures, including those with no visible motor symptoms due to sedation or neuromuscular blockade, which is common in pediatric intensive care units. This is especially important given that seizures occur in 10% to 47% of critically unwell children, with a major portion being electrographic and so unnoticed without EEG monitoring. cEEG is essential not only for detecting seizures but also for measuring cerebral background activity and monitoring therapy outcomes (Friedman *et al.*, 2009). It provides specific information on brain states such as encephalopathy severity and the sleep-wake cycle, all of which are important for prognosis after acute brain trauma, such as cardiac arrest, stroke, or liver failure. Abnormal EEG background patterns, such as burst suppression or attenuated-featureless cycles, are strongly associated with poor neurological outcomes (Benedetti *et al.*, 2023). Quantitative EEG (qEEG) has evolved as a supplementary approach, allowing for large-scale data compression and trend visualization, resulting in faster recognition of seizure occurrence and neurological deterioration (Swaminathan, 2024). Overall, EEG is an important diagnostic and monitoring tool in pediatric epilepsy and broader neurocritical care. Its great temporal resolution, noninvasive nature, and incorporation into real-time clinical decision-making make it indispensable in modern pediatric neurology practice (Abend *et al.*, 2011).

Methods of EEG analysis

Advancements in the study of Electroencephalography (EEG), scientists and medical practitioners can now recognize important patterns in complex brain signals.

Some of the EEG signal analysis methods are given below:

Time-Domain Analysis

Time-Domain analysis involves statistical parameters (mean, variance, skewness, and Hjorth parameters) to effectively recognize transient epileptiform events in the raw amplitude of a signal over time.

Frequency-Domain Analysis

This method uses the Fast Fourier Transform (FFT) and power spectral density estimation to decompose the EEG signals into clinically relevant frequency bands (delta, theta, alpha, beta, gamma) and thus characterize the brain state during the ictal and interictal periods (Kerr *et al.*, 2012).

Time–frequency analysis

Time-frequency analysis solves the problem of the nonstationary nature of EEGs by using Short-Time Fourier Transform (STFT) and Wavelet Transform (CWT/DWT), which provide simultaneous temporal and spectral resolution, especially in pediatric seizure detection (Tzallas *et al.*, 2009; Morales and Bowers, 2022).

Connectivity and Network Analysis

This method quantifies interchannel synchronization and brain-network topology, which is based on metrics such as coherence, Phase-Locking Value (PLV) and graph-theoretic metrics, to establish epileptic network characteristics and seizure onset zones (Centeno and Carmichael, 2014).

Nonlinear and entropy-based analysis

This method is used to measure brain dynamics to distinguish nonlinear measures such as approximate entropy, sample entropy, Lyapunov exponents, and fractal dimensions that enable discrimination between seizure and nonseizure segments that are beyond the ability of linear measures.

Source Localization

Source localization is based on Independent Component Analysis (ICA) and LORETA algorithms, which are used to isolate the neural generators of epileptiform discharges, the main use of which is presurgical planning in refractory cases.

Machine Learning Models for Epilepsy Detection

Machine and deep learning-based analysis uses CNNs, RNNs, LSTM networks or hybrid architectures to achieve end-to-end detection of seizures directly from the raw EEG signal with high sensitivity and specificity (Abbasi and Goldenholz, 2019). Some of the machine learning models are as follows:

Convolutional Neural Networks (CNNs)

CNNs are the most popular, and in addition to their ability to extract input signals, CNNs can perform classification and thus increase the degree of generalization over the intricate aspects of EEG signals. Some studies have shown that 1-D, 2-D and even 3-D CNN models have reasonably high accuracy in detecting epilepsy (Purwono *et al*., 2022).

Recurrent Neural Networks (RNNs)

In the field of Electroencephalogram (EEG) analysis, Recurrent Neural Networks (RNNs) are commonly employed to analyze brain waves over time. EEG signals are continuous time series, and RNNs have feedback loops that allow them to maintain the memory of past states to successfully capture temporal dependencies and predict the temporal patterns of the neural network (Schmidt, 2019).

Generative Adversarial Networks (GANs)

For augmented training datasets as well as improved performance on sparse EEG data, GANs include a generator and a discriminator specifically designed for such purposes. They were first introduced in 2019 and are aimed at predicting epilepsy (Alqahtani *et al*., 2021).

Transfer Learning

This method addresses the shortage of EEG data and reduces training time and resources for deep learning models by applying knowledge from one task to improve performance on a related task (Zhuang *et al*., 2020).

Fusion Modeling

This improves overall model performance by combining various network types, such as CNNs and RNNs. In fusion models, transformers and residual blocks are commonly employed to handle long-term series data and avoid problems such as overfitting and disappearing gradients (Sidek and Quadri, 2012).

Multimodal Learning

This expands beyond EEG signals to include various data types, such as hand, body, and face movements, as well as fNIRS and fMRI, to increase model performance and generate more comprehensive and accurate real-time findings for epilepsy diagnosis (Ramachandram and Taylor, 2017).This bibliometric review aims to comprehensively analyze and summarize the latest advancements in pediatric Epilepsy-focused Electroencephalography (EEG) research, with a focus on the integration of computational neuroscience and clinical practice (Zhang *et al*., 2024). The review includes articles published from 2015-2025, which analyze the use of EEGs in combination with machine learning, deep learning, and other computational intelligence methods for the detection of epilepsy in children. These findings also include a complete bibliometric assessment of publication trends and keywords (Huo *et al*., 2024).

METHODOLOGY

Two well-known scientific databases were carefully examined as part of the search strategy: PubMed and Scopus. To convey the scope of the subject, the following keywords were carefully chosen: "EEG," "Epilepsy," "seizure," "pediatric epilepsy," and "machine learning" in various combinations with Boolean operators (AND/OR) (Wang *et al*., 2025). A structured screening process was used to improve the transparency, reliability and reproducibility of bibliometric analysis. The inclusion criteria for paper selection included peer-reviewed publications published between 2015 and 2025 that particularly addressed the relationships among EEG, computational neuroscience, and pediatric epilepsy. Records that were duplicates, conference abstracts, or related studies were excluded from the screening process. Titles, abstracts and keywords were carefully checked and reviewed for relevance to AI-based EEG analysis in epilepsy. VOSviewer and Python platform was used for the data analysis.

RESULTS

The data from the scientific databased was extracted for the analysis of research trends, collaboration networks and thematic structures. The co-citation analysis identified the collaborations between researchers and institutions, influential publications and the intellectual basis of the field. The main themes of the research and trends within the evolution of keywords were identified with the help of keyword co-occurrence analysis. Figure 1 shows the keyword co-occurrence network, with the size of the nodes reflecting the frequency of the keywords and the links reflecting the co-occurrence relationships. The different clusters are computational approaches (deep learning, seizure detection), clinical evaluation, epidemiological methods and core themes (machine learning, epilepsy). In Figure 2, the overlay visualization in time is depicted, with the color of the nodes representing the average year of publication. Transfer learning and machine learning algorithms are emerging topics that are indicative of increased research interest in advanced computational neurology. The density visualization (heatmap) shown in Figure 3 depicts bright yellow areas as topics with extensive research and cooler areas as topics that are less explored. These analyses collectively illustrate the advancement of epilepsy research into the convergence of AI, neuroscience, and clinical research.

Publication Trends: Research on EEG-based seizure detection via machine learning and deep learning has increased significantly in the last twenty years and has accelerated since 2014, when the use of artificial intelligence in health care has expanded. This is because the 2004-2013 period explored fewer publications and citations, whereas the 2014-2023 period experienced much more growth in terms of the amount of research published and the scientific impact of the research. The highest number of annual publications were issued in 2022, with 261 articles and 6,124 citations. The Web of Science Core Collection (WOSCC) has 1284 articles and 122 reviews about machine learning applications in epilepsy between 2004 and 2023, with an average of 20.14 citations per article. The field of interictal epileptiform discharge detection has become a rapidly growing research area, especially over the past five years, with deep learning solutions as the primary key to new developments.

Keywords evolution

Figure 4 shows the annual evolution of key terms related to EEG studies in epilepsy over the past five years (2018-2026). EEG has the highest and the most consistent frequency of studies of all keywords, which means that EEG is a key tool in epilepsy research. Interest in the field of Seizures has also been evident in research citations over the years. There is a moderate rise in attention for machine learning, indicating the increasing use of AI methods in EEG analysis. On the other hand, pediatric epilepsy has a relatively low and varying frequency in studies, which might mean that this field has not been exhaustively explored and could be a research focus in the future. In summary, this plot provides an overview of the growing role of EEG, seizure detection and machine learning in contemporary epilepsy research.

Geographic Distribution and Leading Countries

Research on machine learning applications in epilepsy has contributed to a total of 87 countries and regions, with the top ten countries contributing almost 70% of the papers. The U.S. had 279 publications, 7,470 citations and the highest percentage of countries collaborating internationally, closely followed by China, with 268 publications and 4,126 citations. India was ranked third in terms of publications (116) and citations (2,178). China had a similar number of publications, but the United States had a greater influence in this field, as evidenced by the greater impact of its publications. Their pivotal role in AI-driven epilepsy research is further underscored by their strong collaborative ties with the United States. The summary information of the leading research institutions in terms of the number of publications and their position in the global collaboration network is presented in Table 1.

Key Journals and Funding Agencies: In the last 20 years, 372 studies on machine learning applications in epilepsy have been published in journals. The leading journals, mostly U.S., U.K.-based and Swiss, published at least 21 articles. The top three sources in this group were Epilepsia (64 publications), Biomedical Signal Processing and Control (44 publications), and IEEE Access (43 publications). Other important journals were Clinical Neurophysiology, Epilepsy Research, NeuroImage and Epilepsy and Behavior. Core journals were responsible for 26.9% (345) of the publications. The research scenario highlights a multidisciplinary transition from conventional research on antiepileptic drugs and genetic mechanisms to sophisticated computational studies that employ artificial intelligence and machine learning methods to predict, detect and manage seizures.

- Thematic analysis: The thematic map (Figure 5) based on PCA shows the following main research themes in EEG research.

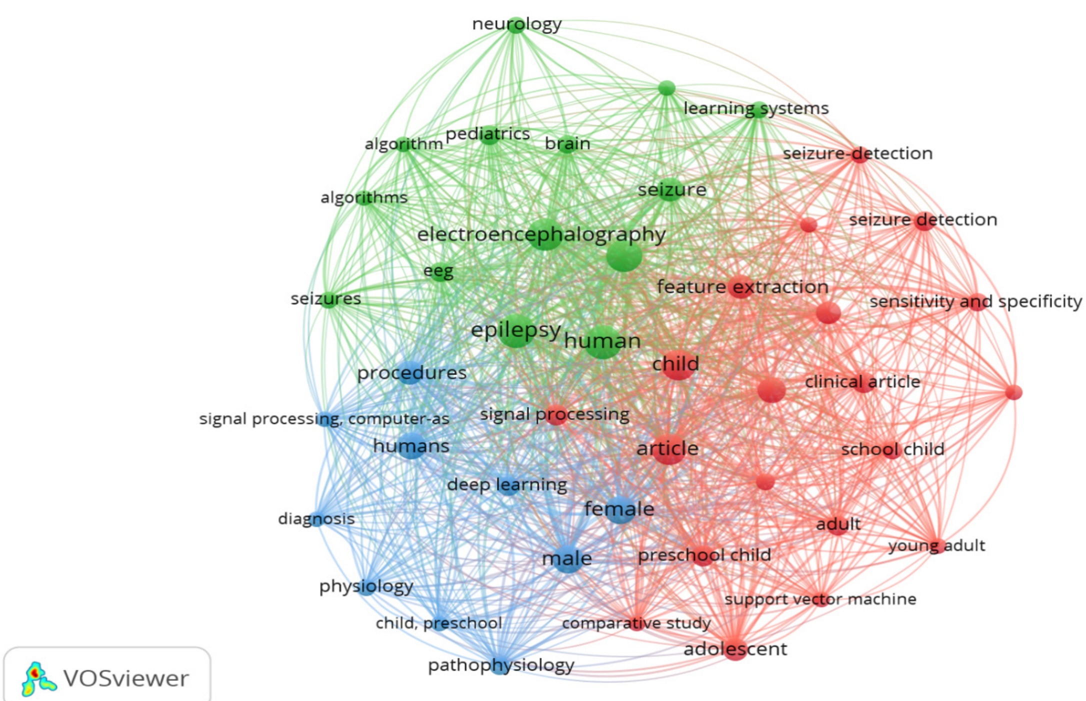

Figure 1: Keyword co-occurrence network in epilepsy and machine learning research.

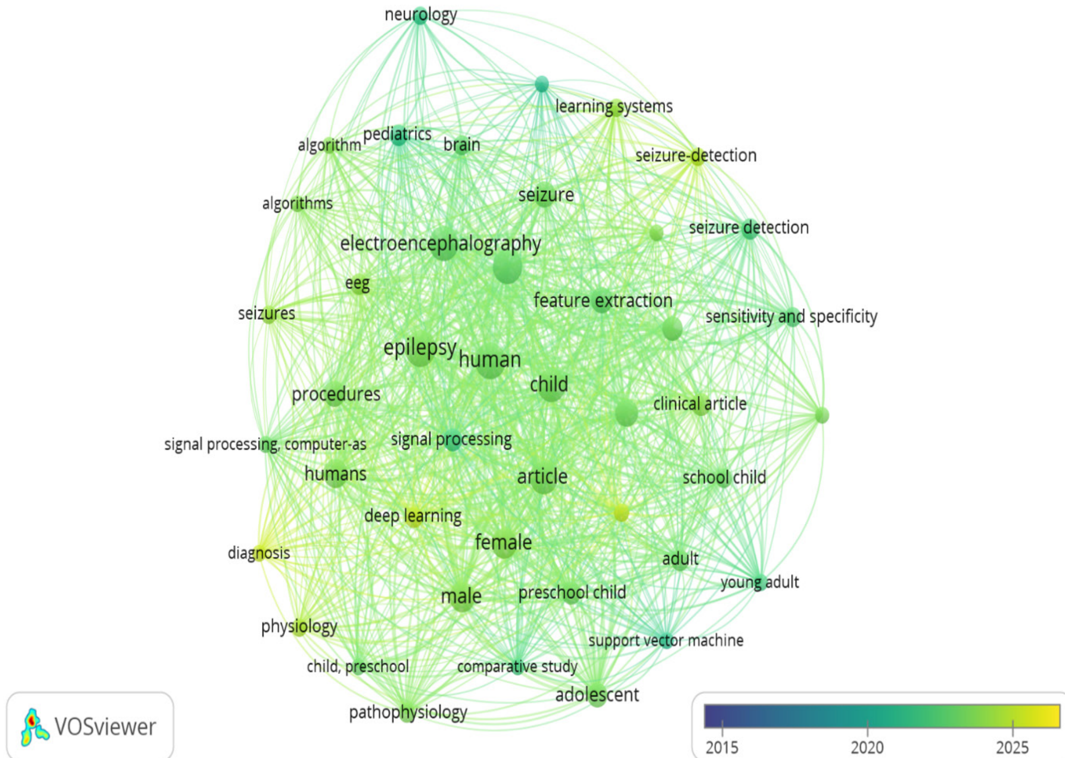

Figure 2: Temporal evolution of keywords in epilepsy and machine learning research (2015-2025).

Table 1: Leading Institutions in EEG Research for Pediatric Epilepsy.

Rank	Institution	Country	No. of Publications	Centrality
1	Harvard University	United States	58	-
2	University of London	United Kingdom	46	0.10
3	University of California System	United States	44	-
4	Harvard Medical School	United States	40	-
5	University College London	United Kingdom	31	-
6	University of Melbourne	Australia	29	-
7	Chinese Academy of Sciences	China	27	0.09
8	Capital Medical University	China	27	-
9	Massachusetts General Hospital	United States	23	-
10	Monash University	Australia	23	-

- EEG Analytics and Machine Learning: Machine learning and EEG are closely linked, and the focus was on using AI for EEG interpretation.
- Pediatric and brain-related studies constitute a specialized research area known as pediatric brain research.
- Signal Processing and Feature Engineering: This involves signal processing, feature extraction, decomposition, and classification techniques in EEG analysis.
- Clinical epilepsy research: Epilepsy-related studies relate clinical neuroscience to computational EEG analysis.
- Seizure detection and Neural Mechanisms: Emphasis on automatic seizure detection, neural networks and attention models in AI.

Importance of keywords: The forest plot (Figure 6) shows the relative importance of the main keywords and the number of times they appeared in research on epilepsy and machine learning. The most dominant themes are indicated by the most highly impactful terms, such as "epilepsy", "EEG" and "seizure detection". The terms "machine learning" and "pediatric epilepsy" have a moderate influence, which is indicative of increased interest in the clinical applications of AI, especially with respect to epilepsy in children. Other terms, such as "classification," "electroencephalography" and "epileptic seizure," are more specific or concentrated areas of research. Overall, the plot clearly shows the significant focus on seizure detection via EEG signals and machine learning methods in epilepsy research.

Table 2 below shows a brief comparative summary table highlighting key machine learning models, datasets, and reported accuracy from studies.

DISCUSSION

The results of this bibliometric analysis support the hypothesis of a paradigm shift in pediatric epilepsy research that is occurring increasingly and involves the gradual replacement of manual EEG interpretation with automated systems using artificial intelligence. The increase in publications since 2014, particularly in 2022, with 6,124 citations and 261 publications, may be attributed to the increase in computational power, greater availability of open-source datasets, and greater awareness of the role of AI in diagnostics among clinicians. The large share of publications and citations in these two countries (US and China) is associated with a concentration of computational infrastructure and a significant research investment. However, although the number of citations

Table 2: Comparative summary table.

Machine learning model	Dataset	Application	Reported performance
Spatiotemporal feature fusion with dual attention	CHB-MIT scalp EEG database	Seizure detection	95.18% accuracy
Convolutional Neural Networks (CNNs)	CHB-MIT scalp EEG database	Automated seizure detection	90-96% accuracy
Bidirectional long short-term memory networks	BONN EEG dataset	Temporal seizure prediction	88-94% accuracy
CNN + attention mechanism	CHB-MIT/TUSZ	Real-time seizure monitoring	92-97% accuracy
Random forest classifier	BONN EEG dataset	EEG signal classification	85-92% accuracy
Support vector machine	BONN EEG dataset	Epileptic vs normal EEG classification	84-95% accuracy

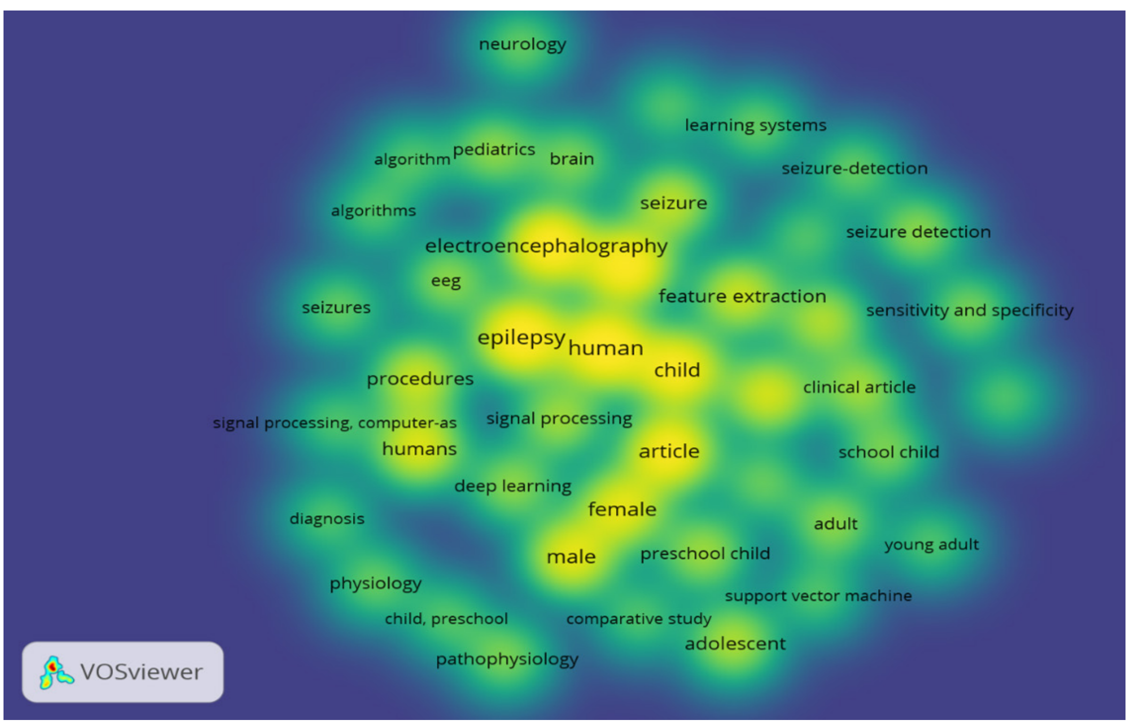

Figure 3: Density visualization of keywords in epilepsy and machine learning research.

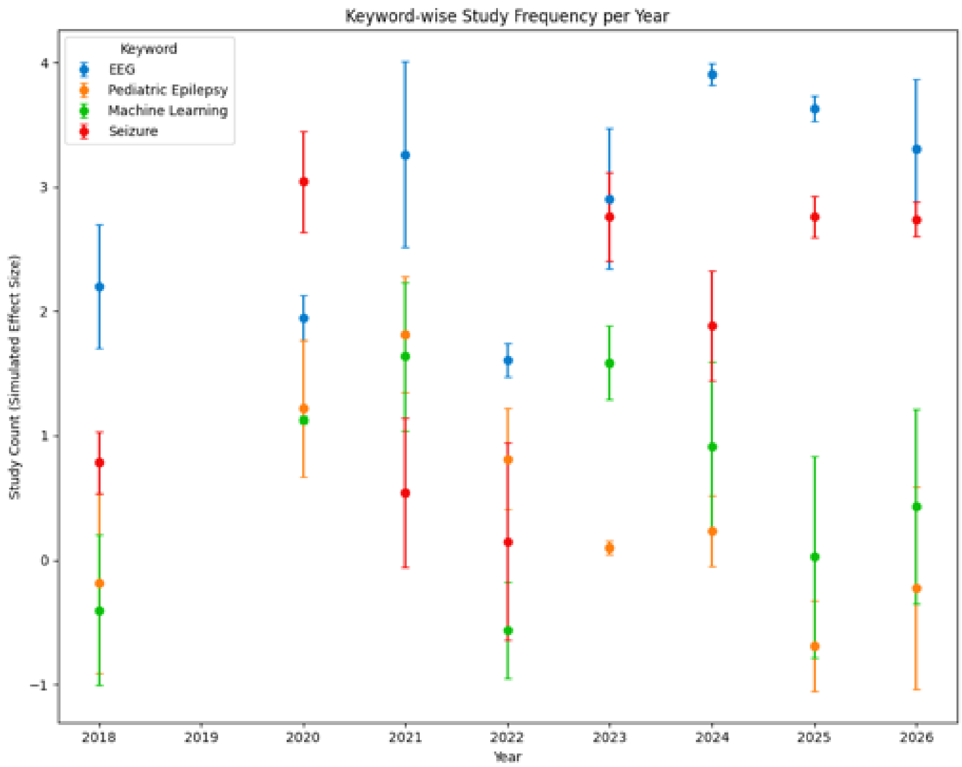

Figure 4: Annual evolution of key words related to EEG studies in epilepsy.

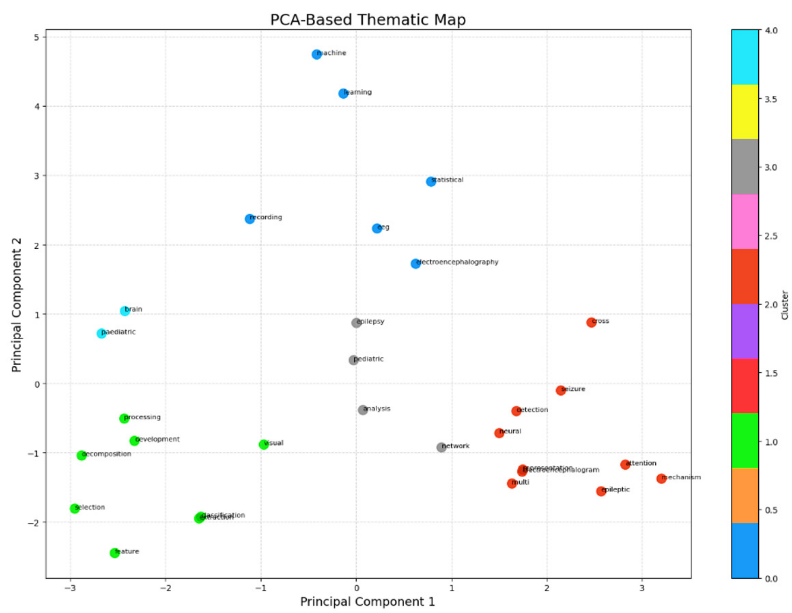

Figure 5: Thematic clustering map via PCA.

during the period was comparable for the two countries, the number of citations in the journal that had the highest number of citations in the world was significantly greater in the United States, indicating a qualitative advantage in terms of the relevance of translation. The appearance of Australian institutions in the top ten highlights the international diversification of this research ecosystem in a progressive manner. From the theme perspective, co-occurrence network and density visualization analyses further emphasize that seizure detection and ML classification of EEG signals form the intellectual core of the field, with transfer learning and multimodal neuroimaging integration quickly emerging at the forefront. The CNN-attention hybrid architectures achieved real-time seizure monitoring accuracies of 92-97%, which are significantly better than those of the conventional SVM and random forest classifiers, which reported seizure monitoring accuracies of 84-92% but are limited by the

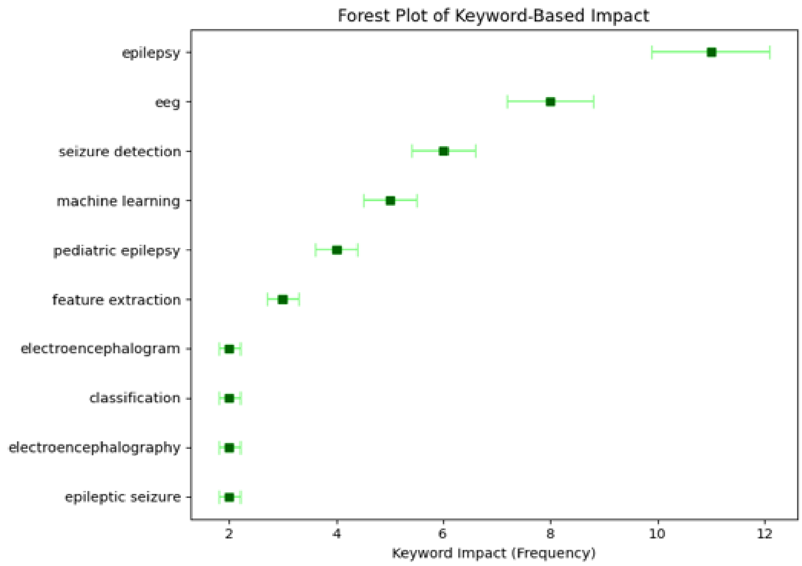

Figure 6: Forest plot for keyword-based impact.

dependency on handcrafted feature engineering and a lack of temporal pattern recognition. However, these strides are offset by several challenges. The extensive use of benchmark corpora (such as CHB-MIT and BONN) reduces generalizability because these datasets do not sufficiently cover the neurophysiologic variability of pediatric populations. Moreover, most successful models have been tested only in laboratory settings offline, and their ability to perform well in a clinical environment (which is contaminated with artifacts and is subject to patient movement) has not been sufficiently tested. This relative lack of representation of pediatric epilepsy as a separate research cluster highlights an ongoing translational gap that should be a clear priority for investigation in the future.

CONCLUSION

This bibliometric and thematic analysis provides a comprehensive overview of the evolution of the concepts and ideas of ML and DL applications over 20 years in EEG-based pediatric epilepsy research. Indeed, the fusion of computational neuroscience and clinical epileptology has resulted in demonstrably powerful diagnostic tools, with state-of-the-art architectures yielding increasingly high seizure detection accuracy, well on the way to clinical deployment. These advances would be a gamechanger for the diagnostic capability in a disorder in which early diagnosis is closely linked to long-term neurological outcome. There are three main challenges that need to be addressed to move mathematical innovation to clinical practice. The first and foremost reason is that there are no large-scale, annotated and pediatric-specific EEG datasets, and models trained mainly from the benchmark corpora of adults cannot truly reflect the neurophysiological diversity of developing brains as a function of age, seizure type, and epilepsy syndrome. Second, as mentioned above, deep learning architecture requires additional interpretability, which represents an important challenge for clinical use: Neurologists cannot simply let opaque models do their work, and the development of Explainable AI (XAI) frameworks is both scientifically important and ethically needed. Third, the lack of prospective multicenter clinical validation studies is a major gap between what they have been shown to do effectively in an experimental setting and how they can be used in a clinical setting. Finally, future research needs to focus on multimodal integration of EEGs with wearable biosensor platforms and neuroimaging platforms, which would allow continuous ambulatory monitoring of seizures in a pediatric setting. Federated learning approaches provide a potential solution for building large, geographically and demographically heterogeneous training sets without compromising data privacy between institutions and regions in the country. Finally, the combination of machine learning and deep learning with EEG analysis is one of the major advancements in modern pediatric epileptology. The scientific basis is very well established; the need for effective and clinically proven implementation in the spirit of responsibility is more urgent than ever before. Collaborative effort at every level-from the computer scientist, the pediatric neurologist, the ethicist, to the regulatory-is needed to enable sustained progress.

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ABBREVIATIONS

EEG: Electroencephalography; **cEEG:** Continuous Electroencephalogram (Continuous EEG); **qEEG:** Quantitative EEG; **fNIRS:** Functional Near-Infrared Spectroscopy; **fMRI:** Functional Magnetic Resonance Imaging; **AI:** Artificial

Intelligence; **ML:** Machine Learning; **DL:** Deep Learning; **XAI:** Explainable Artificial Intelligence; **CNNs:** Convolutional Neural Networks; **RNNs:** Recurrent Neural Networks; **LSTM:** Long Short-Term Memory Networks; **GANs:** Generative Adversarial Networks; **SVM:** Support Vector Machine; **FFT:** Fast Fourier Transform; **STFT:** Short-Time Fourier Transform; **CWT/DWT:** Continuous Wavelet Transform/Discrete Wavelet Transform; **PLV:** Phase-Locking Value; **ICA:** Independent Component Analysis; **PCA:** Principal Component Analysis; **CHB-MIT:** Children's Hospital Boston-Massachusetts Institute of Technology EEG Database; **BONN:** University of Bonn EEG Dataset; **TUSZ:** Temple University Hospital Seizure Corpus; **WOSCC:** Web of Science Core Collection.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interest.

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