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AI-enhanced EEG analysis for clinical decision support in neurology – a mini-review

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Abstract: Artificial intelligence has transformed electroencephalography (EEG) analysis, with publication activity accelerating markedly since 2015 and again after 2022. This trend is driven by transformer-based architectures, foundation models for biosignals, and increasingly accessible open-source tooling. Yet, EEG-based clinical decision support systems (CDSS) only recently gained momentum. A scientific literature scan indicates a sharp rise in EEG-CDSS publications in 2025. This mini-review highlights the technological, regulatory, and infrastructural developments that now make EEG-based CDSS particularly timely and delineates the remaining challenges for their widespread adoption in clinical neurology.

I. Introduction

Electroencephalography (EEG) is a cornerstone diagnostic tool in neurology, yet clinical interpretation remains time-consuming, expert-dependent, and variable [1]. Technological and methodological advances in artificial intelligence (AI) have accelerated research on AI-enhanced EEG analysis since 2015, especially through the adaptation of deep-learning architectures to time-series and biomedical signals. Active research focuses on automated artifact detection, event classification, and disease-specific EEG pattern recognition [2]. AI-enhanced EEG holds tremendous potential to support clinical decision making across epilepsy [3], sleep medicine [4], neurodegeneration [5], and critical care [6]. However, EEG-based clinical decision support systems (CDSS) have progressed far more slowly, highlighting a structural asymmetry between algorithmic innovation and clinical application. This mini-review explores potential explanations and requirements for the translation and adoption of CDSS for EEG in neurology.

II. Material and methods

We conducted a literature scan of two common scientific publication databases (semantic scholar, PubMed, 2005–2025) using combinations of EEG, AI, Machine Learning (ML), deep learning, and clinical decision support keywords. Trends were interpreted qualitatively to avoid over-reliance on inconsistent indexing practices across sources. In addition, we identified contextual factors by reviewing regulatory settings [7,8], landmark AI-method papers for EEG [9−11], and meta-reviews on the adoption of AI in neurology [12].

III. Results and discussion

AI-EEG research displays an accelerated growth since 2022 (Fig. 1), reflecting the cumulative maturation of foundation models, transformer-based signal encoders, improved open-source tooling (e.g., MNE-Python, Braindecode), and greater computational accessibility. In contrast, EEG-CDSS research grew only modestly from 2005 onward, with several plateau phases until 2019. *PubMed* shows a consistent high since 2019 (Fig. 2), the search in *semantic scholar* reveals a peak rise in publications in 2025 (Fig. 1, inset).

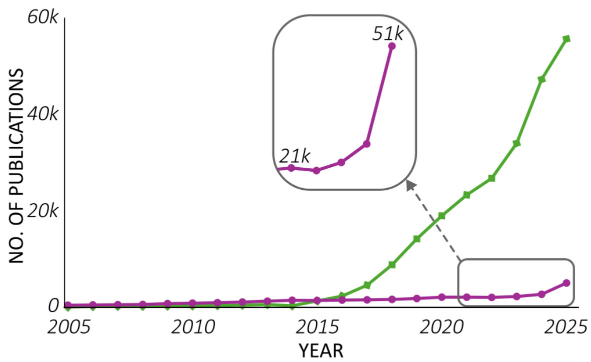

Figure 1: Number of publications per year as found on semantic scholar, search terms "EEG AND (AI OR Machine Learning OR Deep Learning)" (green) and "EEG AND (CLINICAL DECISION SUPPORT SYSTEM)" (purple) [Dec-03-25]

III.I. Explanations for AI and CDSS growth

The application of AI for EEG was fueled by maturing deep-learning architectures suitable for high-dimensional time series and an increase in publicly available, large EEG datasets [10]. Automated preprocessing and evaluation pipelines (e.g., based on the EEG-BIDS standard) further promoted consistency and transparency in analysis [13]. The increasing demand for low-burden EEG screening, driven in part by emerging early-stage therapeutic interventions, creates incentives for automated biomarker extraction [14]. In parallel, recent advances in cloud-based ML platforms and AutoML tools (i.e., automated model selection, training, and evaluation frameworks) have lowered the technical threshold for EEG model development [15].

III.II. Remaining Obstacles

Despite technological and methodological progress, CDSS research faces structural barriers:

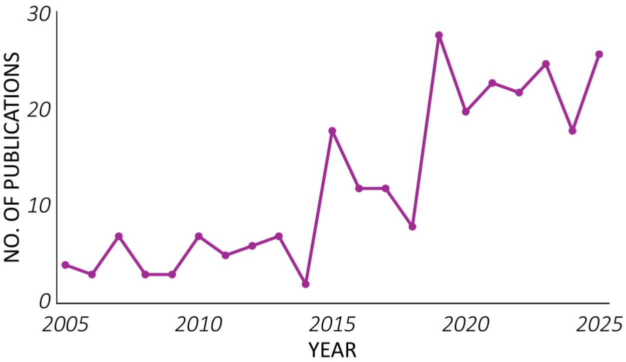

Figure 2: Number of publications per year as found on PubMed when searching for "EEG AND (CLINICAL DECISION SUPPORT SYSTEM)" [Dec-03-25]

Regulatory complexity: Clinically deployed systems must satisfy stringent regulations for medical devices. Until the early 2020s, AI-related regulatory guidance for adaptive AI/ML systems in the USA and the EU remained insufficiently specified. While recent frameworks have reduced uncertainty [7], limited regulatory expertise and capacity in research environments continue to hinder compliance with requirements (e.g., traceability, update control, and algorithmic oversight) and therefore translation into practice.

Lack of trust and interpretability: Deep-learning models for EEG analysis have long been regarded as "black boxes" due to their limited interpretability [11]. Although explainable-AI and post-hoc interpretability methods have advanced, these approaches have so far only partially mitigated this limitation. In practice, it often remains difficult to relate model explanations to established neurophysiological concepts, limiting their clinical interpretability. Persistent concerns regarding robustness, dataset shifts, and susceptibility to artifacts therefore continue to constrain clinical trust in EEG-based CDSS [16].

Data quality and clinical variability: Data heterogeneity continues to impede generalizable CDSS. EEG signals differ across montages and acquisition protocols, while annotation practices introduce additional variability in dataset quality and usability [17]. Artifact contamination remains a challenge, and even large public datasets do not fully reflect clinical diversity. Without harmonized labeling standards and multicenter validation cohorts, model performance may collapse in real-world settings.

Integration burden: EEG systems frequently rely on proprietary formats and restricted interfaces. Many hospital information systems still lack interoperability and cybersecurity requirements further restrict data flow. As a result, the operationalization of EEG-CDSS demands extensive custom engineering, creating economic and logistical barriers to adoption [18].

III.III. Opportunities

Despite these obstacles, the momentum of the field is increasing. Key requirements for progress include (i) establishing large, clinically diverse EEG reference datasets with harmonized annotation standards; (ii) developing neurophysiologically anchored interpretability methods that render model behavior actionable for neurologists; (iii) prospective, multicenter validation studies assessing clinical utility; and (iv) adopting interoperability standards (e.g., BIDS-EEG, FHIR) to streamline CDSS integration into clinical workflows. Aligning these efforts with evolving regulatory frameworks will further reduce translational friction.

IV. Conclusions

While AI-EEG research expanded rapidly, translation into CDSS has been constrained by regulatory, infrastructural, and dataset limitations. Recent increases in EEG-CDSS publications suggest that standing barriers are beginning to dissolve. Future work should investigate how emerging foundation models, explainability methods, standardized EEG datasets, and improved regulatory pathways can enable safe and effective clinical applications.

Author's statement

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