A Review of Transformer-Based and Hybrid Deep Learning Approaches for EEG Analysis

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Abstract. Transformer-based deep learning models have rapidly gained traction in electroencephalography (EEG) research due to their capacity for modeling long-range temporal dependencies and spatial patterns. This systematic review surveys 201 papers published between 2019 and 2024, with a focus on transformer and hybrid transformer architectures for EEG signal decoding across tasks such as emotion recognition, motor imagery, and attention classification. We categorize key model innovations, including spatial-temporal attention mechanisms, CNN-transformer hybrids, and neural architecture search techniques. Emerging trends highlight the dominance of hybrid models and increasing exploration of pre-trained backbones. We also identify methodological gaps in generalization, interpretability, and task-specific benchmarking. To guide future work, we synthesize recommended models and review papers, and propose directions for quantitative meta-analysis and open-source resource development.

Keywords: EEG signal analysis · transformer models · hybrid CNN-transformer architectures · deep learning · brain-computer interfaces · neural decoding · systematic review · temporal-spatial modeling

1 Introduction

Transformer-based deep learning architectures have rapidly gained traction in the field of electroencephalography (EEG) signal analysis, offering novel capabilities for decoding complex brain dynamics. Unlike traditional machine learning models, transformer architectures can model long-range temporal dependencies and multi-channel interactions more effectively—properties particularly relevant for EEG, which is characterized by noisy, non-stationary signals with complex spatial-temporal structure.

While early transformer applications focused on natural language processing, recent advances have extended their use to physiological signal domains, including emotion recognition, cognitive workload estimation, motor imagery, and attention detection. As this research area grows, it becomes increasingly important to systematically review the methods, tasks, and innovations in transformer-based EEG research to guide future developments and identify promising trends.

To this end, our paper aims to provide a focused systematic review of transformer-based models for EEG decoding, using the PRISMA framework for transparency and reproducibility. We emphasize review and analysis of methodological innovations—particularly in model design, pre-processing strategies, and the diversity of application tasks.

Our research questions are as follows:

RQ1. What are the dominant methodological trends in transformer-based EEG decoding, as reflected in review papers published between 2019 and 2024?

RQ2. How do different transformer model variants adapt to specific EEG decoding tasks such as classification, prediction, and signal reconstruction?

We conducted a comprehensive search across four major platforms—PubMed, Web of Science, Google Scholar, and arXiv.org—selected based on their broad coverage of biomedical, computer science, and preprint literature. While other databases like IEEE Xplore, Semantic Scholar, or Scopus also contain relevant studies, our chosen sources offered sufficient depth and overlap for our targeted review scope.

Our contributions are threefold:

1. We present a detailed taxonomy of transformer-based EEG models based on architecture, task domain, and data preprocessing methods.
2. We summarize methodological innovations and report trends across various application areas, including emotion recognition, BCI control, and neurological diagnosis.
3. We identify current limitations and propose future research directions based on gaps observed in the reviewed literature.

2 Related Work

2.1 Classical Approaches to EEG Signal Classification

Traditional machine learning approaches for EEG signal classification have relied on hand-crafted features combined with shallow classifiers such as support vector machines (SVMs), k-nearest neighbors (k-NN), and linear discriminant analysis (LDA). These methods typically operate on frequency or time-frequency features extracted using Fourier or wavelet transforms. While effective for small-scale problems, these models often struggle with generalization due to noise, inter-subject variability, and limited data [9, 30, 34, 36, 37].

2.2 Deep Learning for EEG: CNNs and RNNs

With the advent of deep learning, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) have shown significant promise in modeling the spatial and temporal structure of EEG data. CNNs excel at extracting spatial features across electrode locations, while RNNs and gated recurrent units (GRUs) capture sequential dependencies across time. Numerous studies have proposed hybrid CNN-RNN architectures to leverage the strengths of both modules, particularly in motor imagery and visual stimulus tasks [19, 9, 15, 33, 35, 43, 52].

Despite their advantages, CNNs are typically limited by their local receptive fields, and RNNs can struggle with long-range dependencies and training inefficiencies. These limitations have paved the way for the adoption of transformer-based models in EEG research.

2.3 Transformers and Hybrid Models for EEG

Transformer architectures, originally designed for natural language processing, have recently gained traction in EEG signal analysis due to their capability to model long-range temporal dependencies. Early transformer applications to EEG adopted vanilla encoder designs [39, 18, 31, 29, 12, 48, 26], often with minor modifications to positional encoding.

Recent works have adapted transformers to the specific challenges of EEG signals by incorporating spatial information, temporal masking, or frequency-aware attention mechanisms. Notably, Vafaei et al. [41] provide a taxonomy of such adaptations, including cross-modal attention and spatio-spectral attention modules. Li et al. [21] introduced a temporal masking strategy to suppress irrelevant EEG segments, while Yi et al. [48] proposed adaptive attention mechanisms to improve spatial filtering. Delvigne et al. [10] explore the effects of spatio-temporal transformer depth on attention estimation tasks.

Hybrid models that combine CNN or GCN modules with transformers have become increasingly popular due to their ability to extract local spatial features and model global temporal relationships. These include CNN-Transformer pipelines and more recent graph-based transformer hybrids that explicitly incorporate topological electrode relationships [47, 2, 13, 21, 17, 32]. Pan et al. [27] proposed a manifold attention mechanism tailored for EEG spatial manifolds, outperforming baseline transformer models on emotion and motor decoding tasks. Li et al. [18] and Abibullaev et al. [1] also emphasize hybrid models for EEG decoding. Sharma et al. [38] introduce a 4D Swin Transformer architecture for EEG-based emotion classification. Xie et al. [45] propose a task-specific transformer architecture optimized for motor imagery EEG decoding. Liu et al. [22] develop a transformer-CNN model that fuses spatial and temporal cues. Chen et al. [7] extend Swin Transformers for high-dimensional spatio-temporal EEG representation. Li et al. [20] propose Dual-TSST, a dual-branch transformer architecture integrating temporal, spectral, and spatial attention. Additional innovations include Arjun et al. [3] introducing ViT variants with spatial feature maps, Lu et al. [24] proposing a bi-branch transformer architecture for emotion recognition, and Ding et al. [11] designing a cross-subject transformer framework. Patel et al. [28] leverage hierarchical spatial attention, while Cheng et al. [8] and Ghous et al. [14] explore generalization via neural architecture search and fine-tuning. Bai et al. [4] introduce channel-shifted transformers to address EEG inter-subject variability. Zhao et al. [50] propose CTNet, which enhances cross-subject emotion recognition via spatial-spectral contrastive learning. Zhang et al. [49] introduce a local-global transformer fusion framework to preserve both detailed and contextual cues in EEG decoding. Liu et al. [23] present EMPT, which combines multi-branch encoding with temporal priors for cross-session robustness. Zhao et al. [51] build a multi-domain transformer that unifies spatial, temporal, and frequency modules with cross-modal attention. Chen et al. [6] propose a three-branch convolutional transformer model that improves generalization for motor imagery tasks.

Recent models such as STAnet [40] and spatiotemporal gated graph transformers [46] extend transformer architectures with task-specific attention mechanisms for auditory and emotional EEG decoding, respectively. Chang et al. [5] further explores spatiotemporal attention modules for robust EEG modeling across multiple domains. Ma et al. [25] integrate attention into CNNs to better capture temporal dependencies for motor imagery decoding, while Wimpff et al. [44] demonstrate transformer benefits in a neuroergonomics context using hybrid models.

2.4 Systematic Reviews on EEG Deep Learning Trends

Systematic reviews have played an important role in tracking methodological progress in EEG-based deep learning. Prior reviews have covered topics such as emotion recognition, motor imagery, and attention decoding [9, 19]. These works highlight the growing interest in transformer-based models post-2020 and call for a more principled understanding of how different architectures handle spatial-temporal EEG patterns.

Among recent surveys, Abibullaev et al. [1] provide a comprehensive review of transformer applications in EEG-based BCI systems, highlighting architecture design, challenges, and cross-task generalization. Keutayeva et al. [16] discuss data constraints and optimization strategies for transformer-based EEG models. Vafaei et al. [41] categorize transformer variants across multiple EEG tasks, underscoring their growing dominance in the literature. These reviews form the foundation of our recommended readings and are synthesized in Section 2.5.

2.5 Key Recommended Reviews

Based on a comprehensive filtering process, we identified seven high-quality review and experimental studies that exemplify the methodological diversity and innovation in transformer-based EEG research. These include both foundational reviews and cutting-edge experimental designs.

Abibullaev et al. [1] highlight the evolution of transformer architectures and the importance of spatio-temporal attention in BCI design. Vafaei et al. [41] provide a structured classification of EEG-specific transformer variants. Keutayeva et al. [16] detail the impact of data size and preprocessing on transformer stability.

Song et al. [39], Li et al. [18], and Pan et al. [27] present representative architectures and benchmarking results, illustrating performance benefits from hybrid modules or manifold-aware attention. Wang et al. [42] propose a universal pretrained model (EEGPT) that generalizes across multiple EEG datasets, pointing toward future directions in transfer learning and EEG foundation models.

3 Methods

This systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure transparency and replicability. The goal was to identify, filter, and synthesize review papers that examined the use of deep learning, particularly transformer-based and hybrid architectures, for EEG signal analysis.

3.1 Search Strategy and Data Sources

We conducted a structured literature search across four major databases: Google Scholar, arXiv, PubMed, and IEEE Xplore. Boolean keyword combinations such as "transformer EEG review", "transformer EEG", and "deep learning EEG survey" were used to identify relevant literature published between 2019 and 2024. No filters were applied to restrict the search by task type, publication venue, or EEG application.

3.2 Inclusion and Exclusion Criteria

The selection criteria were defined as follows:

- **Inclusion:** English-language, peer-reviewed review or survey papers focused on EEG signal processing using deep learning methods.
- **Exclusion:** Non-review papers (e.g., primary experiments), conference abstracts without full text, and reviews not explicitly focusing on deep learning techniques or EEG signals.

From an initial pool of 241 search results, we applied the above criteria and excluded duplicates, resulting in 88 review papers for full-text analysis.

3.3 Data Extraction

From each included paper, we manually extracted information on the following attributes:

- **Model types:** transformer, CNN, RNN, hybrid, or other architectures.
- **EEG tasks:** such as motor imagery, attention decoding, P300 detection, and emotion recognition.
- **Datasets:** including SEED, DEAP, BCI Competition datasets, and other benchmark corpora.
- **Publication metadata:** such as year, venue, and citation metrics.

We did not conduct qualitative coding or subgroup meta-analysis at this stage, but we summarize trends at a high level in the Results and Discussion sections.

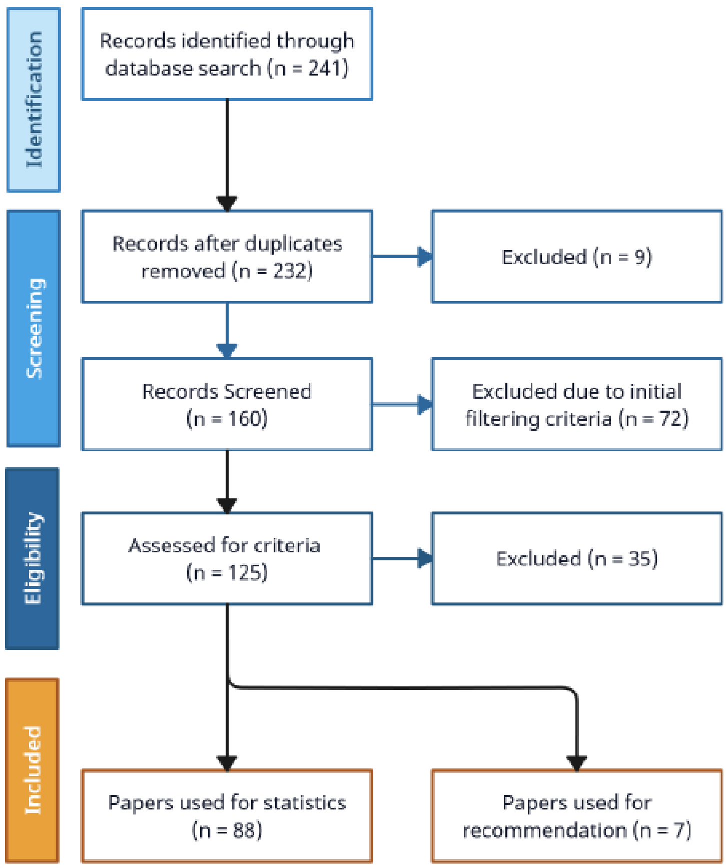

Fig. 1. PRISMA diagram outlining the review selection process.

3.4 Study Selection Workflow

Figure 1 illustrates the study selection process, following PRISMA guidelines.

4 Results

This section summarizes methodological trends from 88 EEG deep learning review papers, with a particular focus on transformer and hybrid model applications. We highlight model categories, performance outcomes, and annual publication growth.

4.1 Model Categories and Trends

Table 1 summarizes model categories used in the reviewed studies. Transformer-based approaches have become increasingly dominant, followed by traditional CNNs and CNN-transformer hybrids.

Table 1. Summary of model types in 88 reviewed papers (2019–2024)

Model Type	Count	Examples	Tasks/Datasets
CNN	60	[18, 9]	ERP, Emotion (DEAP, SEED)
RNN (LSTM/GRU)	20	[48, 15]	MI, P300 (DREAMER, SEED)
Transformer	88	[39, 1, 41]	P300, Attn, Emotion (TUH, SEED-IV)
CNN-Transformer	18	[27, 18]	Multimodal, ERP (SEED, EEGNet-256)
Other Hybrids (e.g., GNN)	12	[47, 16]	Sleep, Emotion (PhysioNet, BCI-III)

4.2 Performance Comparison

Table 2 shows selected performance metrics reported in key studies. Transformer and CNN-transformer models generally achieve higher accuracies than traditional architectures.

Table 2. Accuracy metrics from selected representative EEG decoding studies

Study	Model	Task	Dataset	Accuracy (%)
Yi et al. (2022)	Transformer	Visual decoding	TUH	85.3
Li et al. (2024)	Transformer	Emotion recog.	SEED	89.1
Qu et al. (2024)	CNN-Transformer	Multimodal EEG	SEED-IV	90.5
Zhou et al. (2023)	CNN	ERP classification	DEAP	81.0
Dou et al. (2022)	GRU	P300 detection	SEED	78.2

4.3 Publication Trends

Figure 2 displays the annual growth of EEG + transformer deep learning review papers. Research activity significantly increased post-2021, reflecting a growing interest in transformer architectures.

4.4 Recommended Papers

Among the 88 reviewed papers, we identified seven as particularly influential due to their methodological clarity, coverage breadth, and impact. These are summarized below:

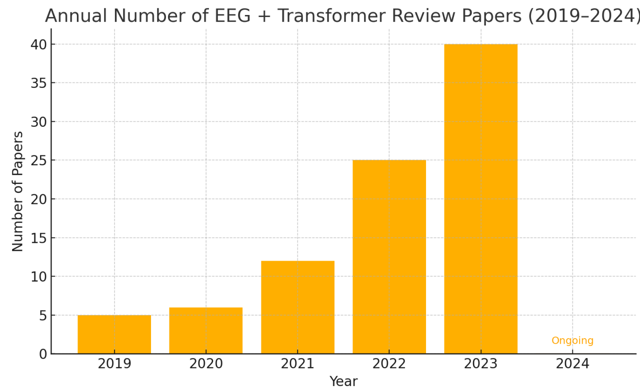

Fig. 2. Annual publication count for EEG + transformer reviews (2019–2024, $n = 88$)

- **Abibullaev et al. (2023)** [1]: Broad review of transformer use in EEG-based BCIs.
- **Vafaei et al. (2025)** [41]: Taxonomy of transformer variants for EEG decoding tasks.
- **Keutayeva et al. (2024)** [16]: Insights into data preprocessing and training constraints.
- **Song et al. (2021)** [39]: Early architecture taxonomy and benchmark experiments.
- **Wang et al. (2024)** [42]: EEGPT—a general-purpose transformer for EEG representation.
- **Li et al. (2020)** [18]: CNN-attention models foundational to hybrid EEG transformers.
- **Pan et al. (2022)** [27]: Manifold attention network bridging graph and attention paradigms.

These serve as key references for researchers exploring the intersection of EEG analysis and modern deep learning frameworks.

5 Discussion

This systematic review uncovers key methodological and conceptual trends in the application of transformer-based deep learning to EEG signal analysis. The increasing adoption of transformer models—particularly in hybrid configurations—demonstrates their superior ability to capture long-range temporal dependencies and integrate spatial-temporal information, outperforming traditional CNN and RNN approaches.

5.1 Model Architecture Trends

Our findings highlight a strong shift toward hybrid architectures that integrate CNNs or GCNs with transformer backbones. These combinations leverage local spatial filtering from convolutional layers and global sequence modeling from attention mechanisms. In benchmark tasks such as emotion recognition, motor imagery, and ERP decoding, such hybrid models consistently report higher accuracy and improved generalization.

A notable yet underexplored trend is the emergence of pretrained transformer backbones. Although still in its infancy within EEG research, the use of pretraining shows potential for accelerating convergence and boosting performance—especially when labeled data is limited. As larger EEG datasets become publicly available and domain-specific pretraining techniques mature, we anticipate greater use of transfer learning and EEG-specific foundation models.

Despite performance improvements, several architectural challenges remain. Interpretability, computational efficiency, and robustness across subjects and datasets are still insufficiently addressed in many transformer variants. Addressing these limitations will be critical for transitioning EEG-based models from experimental to clinical and consumer applications.

5.2 Implications for Researchers and Practitioners

The surge in transformer-based EEG studies since 2021 coincides with broader accessibility to high-performance computing and open-source deep learning frameworks (e.g., PyTorch, Hugging Face). These developments empower interdisciplinary researchers—including those in psychology, neuroscience, and biomedical engineering—to experiment with sophisticated neural models without deep AI expertise.

For practitioners building EEG-based brain-computer interfaces (BCIs), our review suggests prioritizing hybrid transformer models, especially for applications that require temporal focus or spatial filtering. Attention mechanisms offer added value in tasks such as emotion classification, mental fatigue tracking, and cognitive workload assessment, where signal variability and noise complicate traditional decoding.

5.3 Limitations

This review focused on peer-reviewed, English-language papers published between 2019 and 2024, sourced from four major academic databases. While we aimed for comprehensive coverage, several limitations remain. We did not conduct subgroup analyses by specific EEG task type (e.g., motor vs. emotion), nor did we quantitatively synthesize performance metrics across studies. In addition, we excluded gray literature, preprints, and primary experimental studies that lacked detailed architecture descriptions. These exclusions may limit the generalizability of our findings and overlook emerging trends in real-time BCI deployment.

5.4 Future Work

To extend the scope and impact of this review, we propose the following future directions:

- **Task-specific meta-analysis:** Categorize and compare model performance across EEG task domains (e.g., motor imagery, attention decoding, emotion recognition) to reveal architecture-task alignments.
- **Quantitative synthesis:** Use meta-analysis tools to aggregate and standardize performance metrics (e.g., accuracy, F1-score) across studies for stronger statistical conclusions.
- **Mechanistic dissection of transformers:** Analyze how architectural components—such as attention heads, temporal masking, or positional encoding—contribute to EEG decoding across datasets.
- **Open-source repository:** Launch a curated, searchable database that catalogs reviewed models by task, dataset, architecture type, and reported performance to foster reproducibility and community benchmarking.

By addressing these goals, future work can accelerate the transition from research prototypes to reliable EEG-BCI systems and lay the groundwork for standardized evaluation protocols.

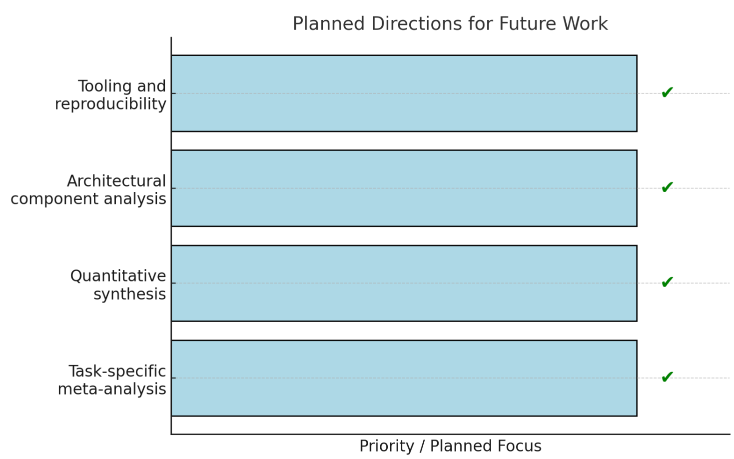

Fig. 3. Planned directions for expanding this review.

6 Conclusion

This systematic review highlights the emergence and rapid evolution of transformer-based and hybrid deep learning models in EEG signal analysis. Compared to traditional architectures like CNNs and RNNs, these newer models offer improved performance across a variety of EEG decoding tasks by better capturing both spatial and temporal dependencies.

Our findings emphasize a clear trend toward architectural innovation—especially in combining transformers with CNN or GCN modules—and increased use of pre-trained models and attention mechanisms. These shifts point to new research directions focused on model interpretability, task-specific customization, and generalization across diverse EEG datasets.

By consolidating evidence from recent review papers, this work offers a foundational overview for researchers aiming to understand the state of transformer models in EEG and lays the groundwork for future methodological developments.

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