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# Mini review: Challenges in EEG emotion recognition

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Electroencephalography (EEG) stands as a pioneering tool at the intersection of neuroscience and technology, offering unprecedented insights into human emotions. Through this comprehensive review, we explore the challenges and opportunities associated with EEG-based emotion recognition. While recent literature suggests promising high accuracy rates, these claims necessitate critical scrutiny for their authenticity and applicability. The article highlights the significant challenges in generalizing findings from a multitude of EEG devices and data sources, as well as the difficulties in data collection. Furthermore, the disparity between controlled laboratory settings and genuine emotional experiences presents a paradox within the paradigm of emotion research. We advocate for a balanced approach, emphasizing the importance of critical evaluation, methodological standardization, and acknowledging the dynamism of emotions for a more holistic understanding of the human emotional landscape.

## Introduction

In the rapidly evolving field of neuroscience and technological integration, Electroencephalography (EEG) has emerged as a pivotal tool, offering profound insights into human brain functions, especially in the study of emotional responses. Emotions, as complex amalgamations of physiological and cognitive reactions, deeply influence our daily interactions, decision-making processes, and even our experiences within architectural settings (Brunner-Sperdin et al., 2012; Nummenmaa et al., 2012; Lehman et al., 2015; Zhang et al., 2022). Emotions play a significant role in shaping human perception and interaction. This makes the study of emotional responses important in various fields, including healthcare and architecture. Understanding these responses is not just academically intriguing; it also has practical implications in these sectors.

Although EEG is increasingly favored due to its non-invasiveness and high temporal resolution, the in-depth analysis of the data it generates is particularly crucial. Numerous studies have underscored the methods of using EEG in emotional research (Chen et al., 2015; Christensen and Abdullah, 2018; Suhaimi et al., 2020; Dadebayev et al., 2021; Li et al., 2022). However, discussions around the quality of EEG emotional measurements are less prominent. While a careful review acknowledges the contributions of these studies, it also unveils oversights, particularly in addressing the intricacies and challenges of EEG data quality. For instance, Cohen et al. (2023) highlights the need for rigorous validation of EEG data in emotional research. These concerns suggest that the allure of high success rates and groundbreaking discoveries might sometimes overshadow the inherent complexities and limitations of EEG, necessitating a more critical examination of its use in emotional studies.

This article explores the complex aspects of emotion research using EEG. It critically examines the claims of high accuracy in the field and discusses the fundamental nature of emotions. The objective is to offer a comprehensive analysis that encompasses the technical challenges associated with EEG data, the impact of equipment and data source variability on application, and the paradoxes faced in conducting emotion research in controlled settings. The paper aims to contribute to a detailed and nuanced understanding of emotional science exploration.

## Methodology

To gain a comprehensive understanding of the challenges and dilemmas in EEG emotion measurement, we embarked on an in-depth literature review in August 2023, focusing our efforts on three pivotal academic databases: Web of Science, Scopus, and ProQuest. These databases were chosen for their extensive coverage in neuroscience and psychological research. Using the keyword combination of "EEG" and "emotion", we aimed to collate core research papers central to our topic. This initial search spanning the years 2022 to 2023 yielded a significant count of 3,741 articles. Recognizing the voluminous nature of our initial pool and the need for stringent quality control, we employed the MMAT (Mixed Methods Appraisal Tool) (Hong et al., 2018) to assess and sieve these articles. The MMAT, renowned for its capability to critically assess mixed methods research, served as a foundational filter in our process.

The subsequent phase of our methodology centered on refining our selection based on the robustness of experimental results. We pivoted our attention toward articles that reported an emotion recognition accuracy rate exceeding 90%, a threshold we deemed crucial as it represents a benchmark in EEG-based emotion recognition that suggests robust and replicable findings. This rigorous criterion distilled our initial list down to 22 quintessential articles poised for an in-depth analysis. To further elevate the quality of our review and to draw comprehensive insights, we employed the bibliometrix packages in R studio for data visualization analysis (Aria and Cuccurullo, 2017). This sophisticated analytical tool enabled us to intricately map co-citation relationships, track research keywords, and intuitively navigate the intricate web of research relationships and emergent themes in the domain, all of which is exemplified in Figure 1.

## The reality behind high EEG accuracy rates

Recent EEG-based emotion recognition research claims strikingly high accuracy rates of 90–99% (see Table 1). These figures are particularly remarkable when juxtaposed with the 75–80% accuracy rate achieved by current facial emotion recognition technology (Naga et al., 2023). However, the majority of these EEG studies employ binary (Valence, Arousal) or ternary (Positive, Negative, Neutral) emotional models, which inherently simplify the classification task and can lead to inflated accuracy rates. For instance, Zhong et al. (2019) reported a drop in accuracy from 79.14–91.67% to 68.26–80.14% when their binary model of emotion

was expanded to include four dimensions. This is particularly telling considering that standard models of basic emotions are often based on six or seven categories, suggesting that a more nuanced approach might yield significantly different accuracy rates.
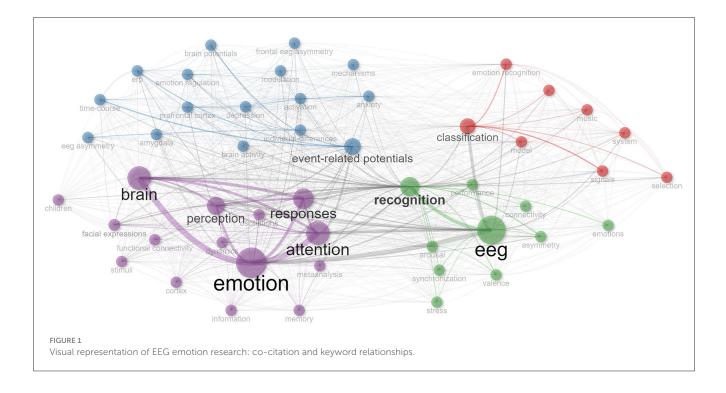
In discussions of EEG-based emotion recognition accuracy, it becomes evident that models relying on subject-dependent data often report higher accuracy rates. This is because when a model is trained and tested on data from the same participant, it can more effectively capture specific characteristics of that individual, leading to increased accuracy. For instance, the BiDANN model by Li et al. (2022) demonstrated an accuracy range of 86.15–96.89% on the SEED dataset (Zheng and Lu, 2015) in a subject-dependent scenario, while the accuracy dropped to 74.52–91.04% in subject-independent settings. Similarly, the BiDCNN model by Huang et al. (2021) achieved emotion recognition accuracy rates of 94.38–94.72% using subject-dependent strategies, which significantly declined to 68.14–63.94% under subject-independent conditions. This phenomenon highlights the substantial reduction in overall accuracy rates when shifting from subject-dependent to subject-independent validation strategies. Independent subject validation poses a greater challenge as it requires the model to generalize to data from unseen participants. This generalization often reveals limitations of the model, as it must capture broader and more universal emotional features rather than merely adapting to specific training data. Therefore, when assessing the true performance of EEG emotion recognition technologies, special attention should be paid to the accuracy rates reported under subject-independent conditions.

The choice of $k$-value in cross-validation significantly impacts the model's generalization ability and accuracy. Although most studies employ 10- or 15-fold cross-validation, which helps to reduce the risk of overfitting to specific data splits, there are situations, such as the use of 5-fold cross-validation, especially when data splits are not sufficiently random or the dataset size is small, where the model may still face the risks of overfitting and artificially inflated accuracy rates. Moreover, the use of windowing and segmentation as data augmentation strategies warrants attention in these studies. When data is augmented through windowing and segmentation, the model may become overly proficient at recognizing repetitive or similar data segments, leading to seemingly improved performance during testing. While this data augmentation strategy can enhance model performance in some cases, it may also lead to poor generalization on new, unseen data, thereby significantly compromising accuracy in practical applications.

Therefore, while it seems that EEG emotion analysis has made significant progress due to deep learning, the high accuracy rates often overshadow the selective presentation of results by researchers under publication pressures.

## The challenge of application

In the field of EEG-based emotion recognition, although there are technical challenges such as physiological disturbances to brain signals from sources like body movement, muscle electrical interference, eye movements, and heartbeats (Fatourechi et al., 2004), the greater challenge lies in applying these techniques

FIGURE 1
Visual representation of EEG emotion research: co-citation and keyword relationships.

to practical scenarios. Unlike facial emotion recognition, which primarily uses images, the data sources for EEG-based emotion detection are more intricate and varied. A notable observation is that most EEG-based emotion recognition studies rely on pre-existing datasets [such as SEED, DEAP (Koelstra et al., 2011), DREAMER (Katsigiannis and Ramzan, 2017)] rather than collecting data independently (Kumari et al., 2022). Furthermore, there seems to be a scarcity of research in applying self-designed and trained models to real-world emotion measurement experiments. Several reasons contribute to this scenario:

- **Lack of standardization in EEG devices:** While image-based facial recognition technologies can often normalize variations through advanced processing, EEG data faces greater challenges in standardization due to the lack of consistent device standards. EEG products can be classified based on the number of electrodes: more than 32 electrodes (high-density systems), 8–32 electrodes (medium-density systems), and fewer than eight electrodes (low-density systems). Additionally, the type of electrode—be it wet, dry, or specialized—adds to the complexity (Hernandez-Pavon et al., 2023). While wet electrodes using conductive gels or saline might offer better signal quality, they can be more cumbersome and intrusive, potentially affecting the emotional state of the participant. On the other hand, consumer-grade EEG devices, typically designed more for entertainment than research, often use fewer electrodes (1–16) and may not be suitable for rigorous scientific study.
- **Challenges in data collection:** Collecting EEG data presents a unique set of challenges, primarily due to the need for specialized knowledge and high-quality capture techniques

(Boudewyn et al., 2023). Unlike more accessible fields like video tracking or facial emotion recognition, EEG data collection demands specialized expertise and sophisticated equipment. Here, "regular researchers" refers to those who might not specialize in neuroscientific methods or lack access to advanced EEG data collection facilities. These general researchers, typically found in broader disciplines without a focus on neurology or bioengineering, often face challenges in acquiring and processing EEG data due to limited facilities or expertise. Such limitations in data gathering can impede the development of robust machine learning models, affecting their generalizability and effectiveness.

Given these challenges, it's clear that emotion recognition based on EEG is not just a matter of recognition technique but also involves the availability of data and equipment. The fragmented nature of data sources, combined with the diversity of EEG devices and the complexities of data collection, poses significant obstacles to the advancement and generalization of EEG-based emotion recognition research.

## The paradox of emotional research

The disconnect between laboratory environments and genuine emotional experiences is a key issue in emotion studies. Laboratory settings may be too rigid and artificial, failing to reflect real emotional experiences in daily life (Russell, 1994). Limitations of laboratory-based emotional research include the simulation of real-life scenarios and individual differences in emotional experience (Rottenberg and Gross, 2007). We need to balance

TABLE 1 Recent EEG emotion recognition studies with an accuracy rate exceeding 90%.

| References | Data set | Model abbreviation | Model description | Signal processing | Emotion type | Dependence accuracy | Independence accuracy | Dependence strategy | Independence strategy |
|---|---|---|---|---|---|---|---|---|---|
| Li et al. (2018) | SEED | BiDANN | Bi-hemispheres domain adversarial neural network | 1D to 2D | PNN | 86.15–96.89% | 74.52–91.04% | TT: 9–6 | 15-fold C-V |
| Yang et al. (2018) | DEAP Koelstra et al. (2011) | CFCNN | Channel-frequency convolutional neural network | 1D to 2D | VA | 90.80–91.03% | Null | 10-fold C-V | Null |
| Ma et al. (2019) | DEAP | Res-LSTM | Multimodal residual LSTM classifier | Downsampling Filtering | VA | 92.87–92.30% | Null | 5-fold C-V | Null |
| Li et al. (2022) | SEED | LSTM-based | Hierarchical spatio-temporal neural network model based on LSTM | Filtering normalization | PNN | 89.05–95.48% | 79.73–90.05% | TT: 9-6 | 15-fold C-V |
| Zhang et al. (2019) | SEED | Riemannian Network | Riemannian Network | Segmentation | PNN | 86.40–91.55% | Null | 10-fold C-V | Null |
| Cho and Hwang (2020) | DEAP | 3D-CNN | 2 types of 3D-CNN models | Segmentation | VA | 99.74–99.73% | Null | 5-fold C-V | Null |
| Zhong et al. (2019) | SEED | RGNN | Regularized GNN model | Filtering Normalization | NSFH (VA) | 71.85–91.92% (90.04–97.60%) | 68.26–80.14% (79.14–91.67%) | 15-fold C-V | 15-fold C-V |
| Zhang et al. (2020) | SEED, MPED Song et al. (2019) | VPR | Heuristic variational pathway reasoning | Filtering | PNN | 93.21–95.67% (SD) 61.61–80.95% (MD) | Null | TT: 9-6 | Null |
| Cui et al. (2020) | DEAP, DREAMER Katsigiannis and Ramzan (2017) | RACNN | End-to-end regional-asymmetric CNN | Segmentation | VA | 96.65–97.11% (DP) 95.55–97.01% (DR) | Null | 10-fold C-V | Null |
| Wang et al. (2020) | SEED, DEAP | EFDMs+STFT | Electrode-frequency distribution maps with short-time | Segmentation | PNN | 88–93% (SD) 79–86% (DP) | Null | TT: 9–6 (SD) TT: 4–1 (DP) | Null |
| Tao et al. (2023) | DEAP, DREAMER | ACRNN | Attention-based convolutional recurrent neural network | Segmentation | VA | 93.38–93.72% (DP) 97.78–98.23% (DR) | Null | 10-fold C-V | Null |

*(Continued)*

**TABLE 1 (Continued)**

| References | Data set | Model abbreviation | Model description | Signal processing | Emotion type | Dependence accuracy | Independence accuracy | Dependence strategy | Independence strategy |
|---|---|---|---|---|---|---|---|---|---|
| Luo et al. (2020) | SEED, DEAP | VAE + GAN | Variational autoencoder and generative adversarial network | Filtering | PNN | 87.5–93.5% | Null | 5-fold C-V | Null |
| Cheng et al. (2021) | DEAP, DREAMER | GcForest | Multi-grained cascade Forest model | Segmentation | VA | 97.69–97.53% (DP) 89.03–90.41% (DR) | Null | 10-fold C-V | Null |
| Liu et al. (2020) | DEAP, DREAMER | MLF-CapsNe | Effective multi-level features guided capsule network | 1D to 2D | VA | 97.97–98.31% (DP) 94.59–95.26% (DR) | Null | 10-fold C-V | Null |
| He et al. (2020) | LabEdata, DEAP | Firefly optimization | A novel firefly integrated optimization algorithm | Filtering | VA | 84.21–96.77% (DP) 91–99% (LabEdata) | Null | TT: 3-1 | Null |
| Huang et al. (2021) | DEAP | BiDCNN | Bi-hemisphere discrepancy convolutional neural network | Segmentation | VA | 94.38–94.72% | 68.14–63.94% | 10-fold C-V | 32-fold C-V |
| Yin et al. (2021) | DEAP | ECGGCNN | GCNN-LSTM hybrid model | 1D to 2D | VA | 90.45–90.60 | 84.81–85.27% | 5-fold C-V | 3*5-fold C-V |
| Zhang and Etemad (2023) | SEED | LSTM-Capsule | Long short-term memory capsule network | Filtering Segmentation | VA | $0.9107 \pm 0.0763$ | Null | 5-fold C-V | Null |
| Fdez et al. (2021) | SEED | CNN | Convolutional neural network | Filtering Normalization | PN\PNN | Null | 91.6% (PN) 79.6% (PNN) | Null | 15-fold C-V |
| Zhu et al. (2022) | SEED | ECN-AF | Emotion classification network based on attention fusion | Filtering Segmentation | PNN | 95.87–96.45% | Null | 5-fold C-V | Null |

PNN, positive, negative, neutral; PN, positive, negative; VA, valence, arousal; C-V, cross-validation; TT, train:test; SD, SEED; MD, MPED; DP, DEAP; DR, DREAMER; Null, not mentioned in the article.

laboratory setups and real-life emotional experiences (Healey et al., 2010).

Experimental equipment may interfere with participants' natural emotional experiences. Advanced devices like virtual reality present potential value and challenges in emotional research, including potential interference with participant emotions (Bohil et al., 2011). Especially with EEG devices, the requirement for participants to remain still to avoid movement interference may restrict natural emotional expression (Wilhelm and Grossman, 2010).

The mismatch between the dynamism of emotions and the fixed nature of experimental design may limit research accuracy and relevance. Emotions' fluidity and change have been emphasized as core parts of research (Kuppens et al., 2010). Time scale issues in emotional research, especially in capturing dynamic emotional changes, have been explored (Davidson, 2010). The complexity of emotional research is revealed with the tension between dynamism and stillness, suggesting EEG devices might be unsuitable as emotional measuring tools.

## Discussion

The use of EEG in emotion recognition research presents a host of possibilities and pitfalls. This confluence of neuroscience and technological integration represents a frontier in our understanding of human emotional processes, yet as our review suggests, researchers need to tread cautiously. The lure of high accuracy rates, the challenges of generalization, and the inherent paradoxes of emotional research have proven to be formidable challenges.

There's no doubt that the temporal resolution of EEG offers a granular view of neural processes as emotions unfold (MacNamara et al., 2022). However, as our review suggests, the translation from granular neural data to accurate emotional recognition is far from straightforward. A primary concern is the reported accuracy rates, which in some instances seem too good to be true. These astonishingly high rates challenge our understanding of the complexities of both EEG data and the nuanced nature of human emotion. High accuracy rates, when not critically examined, can lead to a false sense of progress in the field.

The challenge of application further exacerbates these concerns. Emotion, by its nature, is influenced by myriad factors, from the immediate environment to an individual's past experiences (Jani and Han, 2015). Thus, relying on standard datasets, while practical, may not capture the full gamut of human emotion. The diversity in EEG devices, data sources, and collection methodologies can introduce variability that complicates generalization. Additionally, as mentioned, the lack of standardization in EEG devices makes the reproducibility of research findings a formidable challenge (Keil et al., 2014).

Furthermore, the paradoxical nature of emotional research, especially the gulf between lab conditions and real-world emotional experiences, cannot be understated. Emotions are not static entities to be captured in controlled environments but are dynamically intertwined with our ever-changing contexts (Barrett et al., 2006; Wilhelm and Grossman, 2010). The very act of

measuring emotion in a lab setting might alter the nature of the emotion itself, akin to the observer effect in physics (Russell, 2003). The complexities associated with dynamic emotional changes underline the importance of methodological flexibility and the need for tools that can capture the rich tapestry of human emotions.

## Conclusion

In this comprehensive review, we have shed light on the intricacies of EEG-based emotion recognition. While the allure of high accuracy rates in EEG emotion research paints an optimistic picture, it is essential to approach these claims with cautious optimism. The challenges in generalizing these methods, the inherent discrepancies in laboratory environments, and the dynamic nature of emotions are significant cautions for those eager to adopt EEG in emotion recognition. We must recognize that although EEG holds great potential as a tool in emotion research, its ability to fully understand human emotions is not yet perfect and requires further development and refinement.

## Limitations, implications, and further directions of research

In our comprehensive review of EEG-based emotion recognition, we identified several key limitations and implications for the broader scientific community. Our review, concentrated on literature from 2018 to 2022, may have missed broader developments in the field. Our focus on high-accuracy studies could also have overshadowed valuable insights from moderate or lower-accuracy research. Further, relying on databases like Web of Science, Scopus, and ProQuest could have led us to overlook significant work housed in niche repositories. The highlighted accuracies in studies emphasize the need for a critical evaluation regarding methodological rigor and the clear divergence between laboratory and real-world settings, calling for more standardized and applicable tools and methodologies. Moving forward, there's an evident need to expand the scope of the literature review, hone in on the most effective methodologies, integrate multiple biometric tools for a more comprehensive emotion assessment, prioritize studies with higher ecological validity, and deeply investigate the influence of diverse emotion theories on EEG data interpretation. As we delve deeper into this domain, embracing these considerations could lead to a more nuanced understanding of the human emotional landscape through EEG research.

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ZZ: Conceptualization, Methodology, Visualization, Writing – original draft. JF: Conceptualization, Data curation, Writing – review & editing. LG: Conceptualization, Methodology, Writing – review & editing.

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## Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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