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A Comprehensive Review of EEGLAB for EEG Signal Processing: Prospects and Limitations

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***Abstract*—EEGLAB is a MATLAB-based software that is widely used for EEG signal processing due to its complete features, analysis flexibility, and active open-source community. This review aims to evaluate the use of EEGLAB based on 55 research articles published between 2020 and 2024, and analyze its prospects and limitations in EEG processing. The articles were obtained from reputable databases, namely ScienceDirect, IEEE Xplore, SpringerLink, PubMed, Taylor & Francis, and Emerald Insight, and have gone through a strict study selection stage based on eligibility criteria, topic relevance, and methodological quality. The review results show that EEGLAB is widely used for EEG data preprocessing such as filtering, ICA, artifact removal, and advanced analysis such as ERP, ERSP, brain connectivity, and activity source estimation. EEGLAB has bright prospects in the development of neuroinformatics technology, machine learning integration, multimodal analysis, and large-scale EEG analysis which is increasingly needed. However, EEGLAB still has significant limitations, including a high reliance on manual inspection in preprocessing, low spatial resolution in source modeling, limited multimodal integration, low computational efficiency for large-scale EEG data, and a high learning curve for new users. To overcome these limitations, future research is recommended to focus on developing more accurate automation methods, increasing the spatial resolution of source analysis, more efficient multimodal integration, high computational support, and implementing open science with a standardized EEG data format. This review provides a novel contribution by systematically mapping EEGLAB's usage trends and pinpointing critical technical and methodological gaps that must be addressed for broader neurotechnology adoption.**

***Keywords*—EEGLAB; EEG Signal Processing; ICA; Artifact Removal; EEG Connectivity Analysis.**

I. INTRODUCTION

Electroencephalography (EEG) is an important technique in neuroscience that enables non-invasive monitoring of brain electrical activity with high temporal resolution [1]. EEG has long been used in various clinical applications such as the diagnosis of epilepsy, sleep disorders, and other neurological disorders [2]. In addition, EEG also plays an important role in psychology research, cognitive neuroscience, and the development of brain-based technologies such as brain-computer interface (BCI) [3]. The advantage of EEG over other neuroimaging methods is its ability to directly record neural activity at a relatively low cost [4]. However, the high complexity of EEG signals, especially due to artefacts from muscle activity (EMG), eye movements (EOG), as well as other external disturbances such as electrical artefacts from the surrounding environment, adds to the challenges in EEG data analysis [5]. These conditions make the processing of EEG signals complicated, requiring effective preprocessing techniques and powerful analysis software [6]. Without proper processing, interpretation of EEG data can be severely distorted and reduce the validity of research findings and clinical diagnosis [7].

Reliable EEG analysis software is needed to overcome these challenges. One such software that has become a de facto standard in the global EEG community is EEGLAB [8]. EEGLAB is an open-source MATLAB-based toolbox developed by the Swartz Center for Computational Neuroscience (SCCN), University of California San Diego (UCSD) [9]. Released in the early 2000s, EEGLAB has been widely adopted due to its flexible capabilities, intuitive user interface, and comprehensive and accessible documentation [10]. Key features of EEGLAB include EEG signal preprocessing such as filtering, epoching, re-referencing, and detrending, as well as advanced methods such as Independent Component Analysis (ICA) that are highly effective in separating artefacts from pure neural signals [11]. EEGLAB also offers advanced analysis capabilities such as spectral analysis, time-frequency decomposition, and brain connectivity analysis that allow researchers to explore EEG data in greater depth [12]. Additional plugins developed by the EEGLAB user community further enrich the software's capabilities [13].

However, EEGLAB also has some limitations that need to be considered. Despite its popularity, there has been a lack of recent reviews that systematically assess EEGLAB's technical barriers and its readiness for integration with modern computational neuroscience frameworks, creating a significant research gap. One of the main issues is EEGLAB's dependence on a paid MATLAB license, which is an obstacle for institutions or researchers who have limited resources [14]. In addition, using EEGLAB to manage EEG data on a large scale usually requires high MATLAB scripting skills, which can be a barrier for users with non-technical backgrounds [15]. The issue of inter-format compatibility of EEG data as well as the lack of direct integration with modern machine learning and deep learning techniques are also significant limitations [16]. Therefore, an in-depth review of EEGLAB is needed to clearly identify the software's strengths and limitations. A comprehensive evaluation of EEGLAB's features, technical challenges, and methodological limitations can provide an objective picture of its current state while highlighting the potential improvements needed to overcome these challenges. The main objective of this review is to provide a comprehensive overview of the EEGLAB software by examining its key features, analyzing the challenges experienced by users, and exploring its potential and future development prospects. With a scope that includes a systematic evaluation of the use of EEGLAB in various fields of EEG research, this review is expected to be an important reference for the scientific and clinical communities in developing more effective, efficient, and integrated EEG analysis methods in the future.

II. REVIEW METHOD

A literature search of various academic databases was conducted to find articles related to the use of EEGLAB to support the processing and visualization of EEG data in various neurology-related studies.

A. *Search Strategy*

The search query considers the title, abstract, and keyword sections. The search criteria included four keywords: “EEGLAB”, “MATLAB Toolbox”, “EEG Signal Processing”, and “EEG Research”, which were combined using AND, OR operators. Various databases such as ScienceDirect, IEEE Xplore, SpringerLink, PubMed, Taylor & Francis, and Emerald Insight were queried for research articles published from 2020 to 2024. Table I shows the search queries performed on the selected databases.

TABLE I. SEARCH STRATEGY ON SELECTED DATABASES

Database	Search Query
IEEE Xplore	("EEGLAB" OR "MATLAB Toolbox") AND ("EEG Research" OR "EEG Signal Processing")
PubMed	
SpringerLink	
Taylor & Francis	
ScienceDirect	
Emerald Insight	

The reason for selecting databases such as ScienceDirect, IEEE Xplore, SpringerLink, PubMed, Taylor & Francis, and Emerald Insight in this review is that each provides access to highly reputable scientific journals in the fields of biomedical engineering, neuroscience, information technology, and health sciences. PubMed is particularly relevant for obtaining clinical and biomedical literature related to the use of EEG and EEGLAB applications in a healthcare context. IEEE Xplore and ScienceDirect excel in providing articles related to technology, signal processing, and software development, including the MATLAB toolbox. While SpringerLink, Taylor & Francis, and Emerald Insight offer broad coverage in multidisciplinary research, including aspects of education, cognitive psychology, and software innovation. The combination of these databases allowed for a thorough and representative review of current practices and developments in the use of EEGLAB.

B. *Eligibility Criteria*

In an effort to compile a comprehensive and representative literature review, the selection of articles was made with reference to a number of strict inclusion criteria. Firstly, only articles available in full-text and written in English were considered. This was done to ensure that the content of the articles could be thoroughly analyzed and understood by the international scientific community. Limited access or articles in other languages may hinder the process of data verification, reproducibility of methods, and global relevance of the findings. Secondly, the publication timeframe is limited to the period 2020 to 2024, so that the review results reflect the current state of the use of EEGLAB in EEG research. The world of neurotechnology and EEG signal processing is evolving rapidly, with significant improvements in the integration of machine learning, brain connectivity, and advanced signal processing techniques. Therefore, this time restriction is important to maintain the relevance and topicality of the literature review.

Thirdly, the articles should explicitly mention and use EEGLAB as the primary software in the analysis of EEG data. The main focus of this review is to evaluate the strengths and weaknesses of EEGLAB specifically, not to discuss EEG software in general. Therefore, articles that only briefly mentioned EEGLAB or did not explain its use in analysis were not included in the review. Fourth, the context of EEGLAB application in the article should be clear and relevant. EEGLAB should be used within the framework of real EEG research or applications, such as in clinical studies (e.g. epilepsy, sleep disorders, or intraoperative neurophysiological monitoring), as well as experimental research involving cognitive processes, emotions, perception, or motor control. Articles using EEGLAB in interdisciplinary fields such as neuropsychology, neuroinformatics, and artificial intelligence (AI) are also included, as long as the use of EEGLAB plays a central role in the data analysis process. By applying these four criteria, the review is expected to produce a literature mapping that is not only comprehensive, but also has a strong focus, methodological quality, and scientific significance in understanding the utilization of EEGLAB in the context of modern EEG.

C. *Study Selection*

In conducting this review, we used Rayyan, a web-based tool designed to efficiently support the systematic review process. Rayyan was chosen for its ability to quickly sift and organize the literature, as well as its collaborative features that support simultaneous teamwork. One of Rayyan's key functions that was particularly useful was the ability to identify and remove duplicate records from multiple databases. Thus, we were able to build a unique and clean reference database as the basis for the subsequent article selection process. The article selection process followed the three-step method recommended in the systematic review literature [17], and was applied consistently to ensure objectivity and transparency, as presented in the flow diagram in Fig. 1. The first step was an assessment of article titles to quickly filter out publications that were not explicitly related to the topic of EEGLAB or EEG signal processing. This stage aims to reduce the workload in later stages by eliminating entries that are clearly not relevant.

The second step was a review of the abstracts and keywords, which allowed an initial identification of articles that might fulfil the inclusion criteria based on the scope of their content. The focus on this section provided an initial overview of the context, methodological approach, and the extent to which EEGLAB was used substantially in the study. Only articles that showed relevance and potential for further review proceeded to the third step. The third step was a full-text analysis of the pre-selected articles. At this stage, we conducted a thorough evaluation of the content to assess its compliance with the pre-defined inclusion criteria, including details of EEGLAB usage, the context of EEG application, and the validity and relevance of the study findings. This process allowed us to assess the quality and depth of each article's contribution to the topic. Finally, after going through the three-stage selection process, we compiled a final database of articles that met the eligibility criteria. This set of references became the main foundation for the content analysis and synthesis of the results in this review. This systematic approach is expected to minimize selection bias and enhance the reproducibility and credibility of the review results we present.

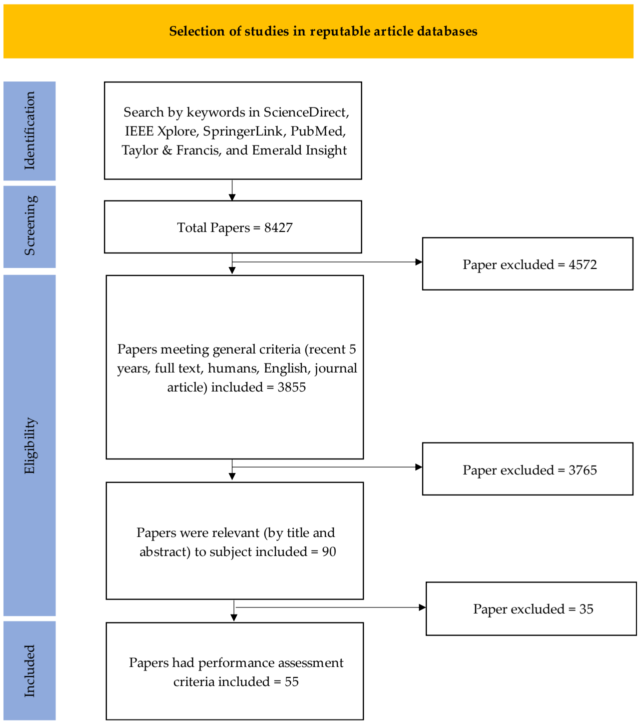

Fig. 1. PRISMA flow diagram & screen

D. *Quality Assessment*

In the process of assessing the quality of the articles included in this review, five main criteria were used, which were aligned with the principles of systematic evaluation in EEG research, particularly regarding the use of EEGLAB software. The first criterion was clarity of purpose and research question, which required each article to have an explicit focus and clearly outline the goal or hypothesis to be achieved. This is important to assess the extent to which the use of EEGLAB supports the scientific goals of the study. The second criterion is transparent design and methodology, where articles are assessed based on the clarity in describing the stages of EEG analysis, including preprocessing methods, use of ICA, signal segmentation, as well as parameters used in EEGLAB. Studies that present a detailed methodology are easier to replicate and evaluate objectively. The third criterion is the validity of the use of EEGLAB, i.e. the extent to which EEGLAB was used substantially in the study. Articles that only mentioned EEGLAB without explaining its application were not considered to fulfil the quality expected in this review. Therefore, only studies that documented the actual and technical functions of EEGLAB in the EEG analysis process were accepted.

The fourth criterion focuses on clear and measurable reporting of results. Articles should present quantitative and interpretable EEG analysis result data, such as time-frequency results, power spectral density values, or ICA metrics. Complete reporting of results reflects the quality and real contribution of using EEGLAB in supporting scientific findings. Finally, discussion and study limitations are also important indicators in quality assessment. A good article should include a critical discussion of the results obtained, as well as mention the limitations of both the technical use of EEGLAB and the overall study methodology. Openness to these limitations demonstrates scientific integrity and provides a direction for further development for future users of EEGLAB. The following is the number of articles related to the use of EEGLAB in EEG signal processing from selected databases published between 2020-2024 as a result of the quality assessment.

Of the total publications that have gone through the quality assessment process (Fig. 2), it can be seen that the Taylor & Francis database accounts for the largest number of articles, with 24 articles, signalling the dominance and high concentration of publications related to this topic in journals under Taylor and Francis. This was followed by Science Direct with 13 articles, indicating that this platform is also an important source of EEGLAB-related literature. Other databases such as IEEE and SpringerLink contributed 7 and 5 articles respectively, reflecting significant participation from the engineering and computer science communities. Meanwhile, PubMed recorded only 4 articles, which may indicate that the use of EEGLAB has not been widely reported in biomedical-based clinical medical literature. Emerald Insight contributed the smallest number with 2 articles, suggesting a more limited relevance in this topic. This distribution indicates that the focus of EEGLAB-related research is found more in engineering-orientated journals, cognitive psychology, and experimental neuroscience, compared to purely clinical medical journals.

In addition, Fig. 3. presents the distribution of articles from selected databases by publication year between 2020 and 2024. There is a significant upward trend in the number of publications discussing the use of EEGLAB for EEG signal processing over the five-year period. This distribution reflects the growing interest and increased research activity in the field of EEGLAB-based EEG signal processing, most likely triggered by the increasing adoption of neuroinformatics technologies and the need for more efficient and flexible EEG data analysis. This trend also indicates that EEGLAB is gaining relevance in the scientific community and becoming an important tool in interdisciplinary EEG research.

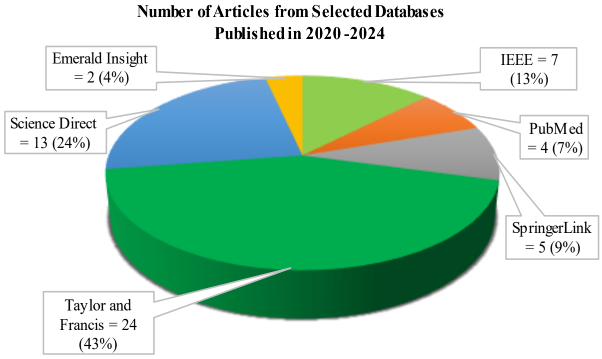

Fig. 2. Number of articles from selected databases

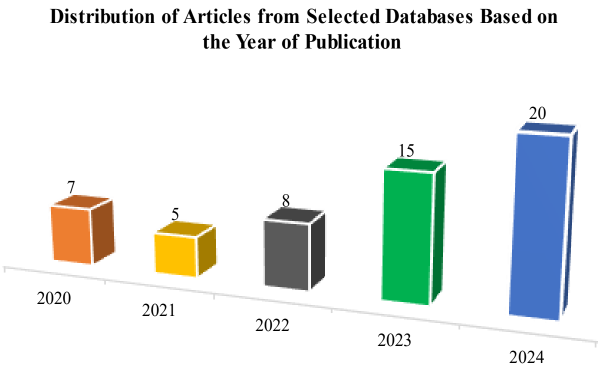

Fig. 3. Distribution of articles based on the year of publication

III. EEGLAB FOR EEG SIGNAL PROCESSING

Several studies have shown that EEGLAB is widely used for EEG data analysis in experimental and clinical studies, with the application of techniques such as filtering, re-referencing, and ICA. For example, Hirth *et al.* [18] utilised EEGLAB to analyse upper arm motor performance with 64-channel EEG, but did not explicitly explain its limitations. Jing *et al.* [19] also used EEGLAB on driver fatigue data with 8 channels, focusing on spectral and topographic analyses. Meanwhile, Schade *et al.* [20] examined the effect of EEG stimulation with habituation and sham protocols on 10 channels, with features such as FFT and PSD, but also did not review the limitations of the platform. In a more complex case, Mahdid *et al.* [21] evaluated EEGLAB with various EEG systems, ranging from 8 to 128 channels. They found that ICA on EEGLAB is suboptimal for systems with low channel counts, and that topographic visualizations such as topo plots have limitations in handling uneven electrode distributions. King *et al.* [22] pointed out limitations in terms of automation and real-time analysis when using EEGLAB in time stress studies. They mentioned that although features such as ERSP and time-frequency analysis were available, artefact detection was still done manually.

Other studies highlighted specific limitations in the context of the population or device. Vesoulis *et al.* [23] explicitly did not use EEGLAB because they considered that the toolbox was not suitable for neonatal EEG, mainly due to limitations in handling restricted channels and non-adult data characteristics. Similarly, Chen *et al.* [24] showed that EEGLAB's ICLabel was not effective in detecting multisource artefacts in ictal EEG data from epilepsy patients, especially when the number of channels was limited. Meanwhile, Moliadze *et al.* [25] and Zhou *et al.* [26] used EEGLAB in ASD and Herpes Zoster studies, but did not provide a critical evaluation of its performance or limitations. Similarly, a study by Mehmood *et al.* [27] who used EEGLAB for ERP generation in children with special needs. Some studies tried to extend the use of EEGLAB with additional integrations. Thompson *et al.* [28] combined EEGLAB with FieldTrip and SleepSMG toolboxes, but noted that the integration still had to be done manually. Cancino *et al.* [29] added the NSG plugin for integration with HPC-based computing, but recognised that EEGLAB is not optimal for big data due to low transfer rates and high parallel overhead. García *et al.* [30] and Niu *et al.* [31] utilised EEGLAB for preprocessing and microstate analysis, including coverage and occurrence calculations. However, they also indicated that EEGLAB does not support the BIDS standard and features such as nested cross-validation, which are important for multivariate decoding studies.

The use of EEGLAB in cognitive experimental research was also seen in studies by Pozharliev *et al.* [32] and Fuhrmeister *et al.* [33]. Both applied EEGLAB to a population of university students and German speakers, respectively to process EEG signals in business and linguistic affection contexts. They used standard features such as filtering, ICA, segmentation, and eye artefact analysis (SASICA). However, like many other studies, the limitations of EEGLAB were not explicitly spelled out, signalling a possible lack of critical evaluation of the technical aspects of data processing. In the motor experimental study by Mushtaq *et al.* [34], EEGLAB was used for a rapid arm-reaching task with 64-channel EEG, including filtering, rereferencing, ICA with Infomax algorithm, as well as baseline correction and integration with FieldTrip. Although limitations are not described, the use of full features and external integration reflects the flexibility of EEGLAB for neuromotor tasks. In a clinical context, Lopes *et al.* [35] used EEGLAB to analyze EEG signals from epilepsy patients and healthy subjects, focusing on IC labelling and PSD visualization. They highlighted that the ICLabel plugin used did not utilize the IC time-series information, thus reducing the accuracy of component classification. This suggests that although EEGLAB provides an automated labelling artefact tool, its classification reliability can still be improved with a time-based approach.

In the pediatric population, Harwood *et al.* [36] used EEGLAB with the PREP pipeline for ERP analysis of 128-channel EEG. This study did not mention any limitations, although the complexity of early childhood data should require robust artefact validation features. Bi *et al.* [37], in an anesthesia study, noted that EEGLAB is less efficient for analyzing large-channel data such as 256-channel, particularly when used for coherence analysis and sparsity representation. The pseudo-EEG simulation study by Pellegrini *et al.* [38] and the use of multi-conditioning by Caetano *et al.* [39] show that EEGLAB can be integrated with the ROIconnect toolbox and AAS methods. However, Caetano notes that artefact processing in EEGLAB is not efficient for real-time applications, marking a limitation to real-time-based neurofeedback or BCI applications. Large-scale research such as by Bailey *et al.* [40] highlighted the weakness of the ICA algorithm in EEGLAB for ERP analysis with slow signals (<1 Hz). They also used various plugins such as ICLabel, PREP, wICA, and MWF, which showed the need for strengthening artefact cleaning features in complex scenarios. On the other hand, Rashmi *et al.* [41] highlighted the weakness of EEGLAB in terms of user interface, which is considered unfriendly for beginners due to the less intuitive GUI.

Meanwhile, Coyle *et al.* [42] utilised EEGLAB for connectivity analysis in mTBI patients and healthy controls. Although its limitations were not spelled out, its use for wPLI power and connectivity analysis demonstrated the compatibility of EEGLAB for clinical neurophysiological studies. The study by Simfukwe *et al.* [43] with 890 subjects also showed that preprocessing with ICA and ASR was still predominantly done manually, emphasising the need for a more robust automated pipeline. Jianbiao *et al.* [44] on tinnitus patients also found that EEGLAB did not support advanced non-linear signal analysis and ICA required manual curation. In the ICU EEG study by Hbibi *et al.* [45], although EEGLAB supports advanced plugins such as AMICA, REGICA, and AAR, manual intervention is still required and there is no support for thorough multifractal analysis. Gao *et al.* [46] again showed that for real-time applications, such as the use of the FMRIB plugin (AAS method), EEGLAB is not ideal without extensive manual preprocessing. This confirms that although EEGLAB is highly modular, its optimal use still demands high technical involvement and limitations in straightforward processing scenarios.

Several large studies in clinical populations have again highlighted the challenges of EEGLAB in handling multichannel data and the need for more comprehensive functional analyses. Simfukwe *et al.* [47] analyzed 534 subjects with 19-channel EEG and noted the limitations of EEGLAB in describing functional coherence between brain locations. This was reinforced by Zhou *et al.* [48] in a migraine study, where although EEGLAB was used for segmentation and automatic artifact removal (AAR), the artefact detection process remained manual and not real-time. Likewise, Wu *et al.* [49] in their post-stroke fatigue study stated that artefact inspection was done visually and EEGLAB does not yet support connectivity analysis directly, underlining the limitations in the brain network exploration pipeline. The study by Mazzeo *et al.* [50] on patients with subjective cognitive decline (SCD) reflects the complexity of the practice of using EEGLAB. They implemented various functions such as PREP, ICA, ICLabel, and microstate analysis, but acknowledged that the pipeline is still highly dependent on manual inspection and does not yet support machine learning flow natively. Meanwhile, Kawar *et al.* [51] who examined the EEG of ADHD children pointed out that EEGLAB does not yet have a sufficient automated artefact cleaning system for the pediatric population, where noise tends to be higher and more varied.

In the context of chronic pain, Knoph *et al.* [52] noted that EEGLAB was used for ERP extraction and IC labelling in chronic pancreatitis patients, but the process relied heavily on visual inspection and did not include non-linear EEG analysis. While Zhao *et al.* [53] who examined brain activity in adolescents with depression used EEGLAB for ERPs, the pipeline still relied on manual ICA and did not support real-time processing, which is important for interventional or neurofeedback applications. The study of Taberna *et al.* [54] with 128-256 EEG channels in various tasks (resting, visual, motor) underlined that EEGLAB is not ideal for large-scale datasets due to the large number of stages that require visual inspection and non-automated artefact removal. In an explorative study by Cannard *et al.* [55], although EEGLAB was used alongside the BrainBeats plugin for heart-brain signal analysis, the platform does not support full integration with other physiological signals such as ECG or PPG. This is a real limitation for multimodal studies.

Kalburgi *et al.* [56] used EEGLAB for microstate analysis in resting-state with eyes open and closed. However, no limitations were mentioned, although this approach usually requires very sensitive artefact detection and segmentation. Mondellini *et al.* [57], in a VR-based cognitive workload study, noted that EEGLAB does not provide non-linear features or brain connectivity, whereas indices such as MWLI can be affected by complex neural network interactions. Hsieh *et al.* [58], using EEG for the Flanker task, reported that the configuration and validation of artefacts is highly manual, and there is no effective automated validation for non-ocular artefacts. In the study of Niedernhuber *et al.* [59] with only 7 EEG channels, EEGLAB was still used for Hilbert transform and power analysis, but did not support automatic integration with phenomenological experience time-tracking (TET) methods, which are important in consciousness research. Vourvopoulos *et al.* [60] attempted to combine EEG with a VR environment for stroke rehabilitation, using a combination of complex preprocessing. They noted that EEGLAB does not support direct multimodal integration, such as data synchronization with fMRI or VR systems. Simfukwe *et al.* [61] again highlighted the issue of automation limitations, although the pipeline includes ICA, ASR, and relative PSD analysis, artefacts still cannot be fully eliminated automatically, and there is no support for integration of additional biomarkers.

In the field of integration of wearable EEG and portable BCI systems, Niforatos *et al.* [62] evaluated two systems: BCIglass (3-channel) and Enobio 20 (20-channel). They used EEGLAB for thorough preprocessing, including ICA and ICLabel, but noted that the ICA process still had to be done manually, and that EEGLAB did not yet support direct integration with head-mounted displays (HMDs), and its application was limited to real-time scenarios. This highlights the challenges of EEGLAB in addressing the needs of today's portable and interactive technologies. Pasqualette *et al.* [63], in their emotion- and social context-based ERP study, showed that although EEGLAB is capable of comprehensive ERP preprocessing and analysis using CleanLine, PREP, and ICA, it requires additional integration for synchronisation with eye-tracking systems, and artefact rejection is not yet fully automated. Similarly, Miras *et al.* [64] developed a dedicated tool outside of EEGLAB to calculate the fractal dimension index (FDI), pointing out that EEGLAB does not directly support advanced analytical features such as fractal modelling and source-space reconstruction without additional software.

Rehabilitation-based clinical research by Kumari *et al.* [65] showed that although EEGLAB is effective in the analysis of ERSP and power bands of spinal cord injury (SCI) patients, the preprocessing process is still not automated, and EEGLAB is not capable of supporting real-time integration with functional electrical stimulation (FES) systems. These limitations hinder the utilizations of EEGLAB in the development of closed-loop systems or adaptive neurofeedback. Zur *et al.* [66] used EEGLAB to explore space perception and positive affect in an architectural context. Analyses included mu-rhythm, theta power, and dipole fitting, but preprocessing relied heavily on manual processes. The use of external plugins such as ICLabel also remains necessary, and the artefact detection process has not been automated, which is problematic in studies that rely on accurate spatial representation of EEG. In the domain of sleep and respiratory disorders, Zhang *et al.* [67] used 6-channel EEG from OSA (obstructive sleep apnoea) patients. They utilised EEGLAB for filtering and signal transformation, but noted that EEGLAB does not support full integration with PSG (polysomnography) systems, and many preprocessing stages are still semi-automated. This reflects the limitations of EEGLAB in multimodal sleep studies.

Kim *et al.* [68] assessed the regional contribution of EEG to dementia classification using PSD and ASR, but stated that EEGLAB requires an external plugin for microstate analysis and the artefact detection process is not yet fully automated. Similar limitations were mentioned by Chen *et al.* [69] who studied migraine patients, where ICA had to be manually confirmed, the pipeline was not yet fully automated, and there was no integration of non-linear analysis. The study of Wojtecki *et al.* [70] in Alzheimer's patients added that although EEGLAB is used for spectral and entropy analysis (Tsallis), the artefact removal process is semi-automated, and EEGLAB does not yet support multimodal biomarker estimation such as MRI and cerebrospinal fluid (CSF). This limits its use for comprehensive neurodegenerative research. Finally, Li *et al.* [71] and Korochkina *et al.* [72] closed the series of studies with a focus on emotion regulation and semantic integration in memory. EEGLAB was used for frontal alpha asymmetry and ERP analyses, but both highlighted that artefacts are cleaned semi-automatically, and EEGLAB does not support more complex connectivity or integration semantic mapping features. The following is previous research related to the use of EEGLAB in EEG signal processing, as shown in Table II.

TABLE II. PREVIOUS RESEARCH USING EEGLAB IN EEG SIGNAL PROCESSING

No	Author & Year	Dataset	Use of EEGLAB	Limitations of EEGLAB
1	Hirth *et al.*, 2020 [18]	15 healthy participants (upper limb motor performance); 64-channel	Filtering; Resampling; Re-Referencing; ICA; dipole fitting	Not explained
2	Jing *et al.*, 2020 [19]	9 driver (driving fatigue state); 8-channel EEG	Preprocessing; ICA; PSD; topomap	Not explained
3	Mahdid *et al.*, 2020 [20]	1 subject (128-channel EGI; 30-channel Cognionics; 24-channel wearable sensing; 14-channel EMOTIV; 8-channel OpenBCI)	Filtering; Re-Referencing; Clean data; Power Spectral and Topography; Functional Connectivity	ICA less effective for few channels; Biased towards high-density systems; Limited topoplot for uneven electrode distribution
4	Schade *et al.*, 2020 [21]	8 participants (Habituation, Sham, Disruptive, Enhancing); 10-channel	Re-referencing; Epoching data; artifact rejection; FFT; PSD	Not explained
5	King *et al.*, 2020 [22]	16 healthy subjects (normal vs. time pressure); 34-channel	Filtering; downsampling; artifact rejection; ICA; Dipole fitting; ERSP; topography; time-frequency	Analysis is not real-time; artifact detection remains manual
6	Chen *et al.*, 2020 [23]	Mesial temporal lobe epilepsy patient; 21-channel ictal EEG	Data visualization; preprocessing; ICA; time/frequency decompositions	ICLabel not suitable for non-ICA; Difficult to detect multisource artifacts; Less effective for few-channel EEG
7	Moliadze *et al.*, 2020 [24]	14 ASD and 12 neurotypical controls	ICA preprocessing (extended infomax)	Not explained
8	Cancino *et al.*, 2021 [25]	Public dataset from OpenNeuro.org; 70-channel	ICA; preprocessing; topoplot; nsgportal plug-in; integration with HPC/NSG	Not optimal for big data; Slow upload/download; High parallel overhead; Does not support interactive processes
9	Piper *et al.*, 2021 [26]	34 Italian participants (stimulus alcohol drinks with different calorie content); 16-channel	Signal preprocessing (filtering, artifacts); Valence calculation (α & β power); Signal decomposition; EEG with wavelets	Not explained
10	Zhou *et al.*, 2021 [27]	71 Herpes Zoster (HZ) patients and 71 healthy controls; 16-channel	Bandpass filter; rereferencing; artifact removal; ICA	Not explained
11	Mehmood *et al.*, 2021 [28]	60 children (30 control, 30 special); 14-channel	Bandpass filtering; ICA; ERP generation & LPP analysis; Brain cluster visualization & grand average study	Not explained
12	Thompson *et al.*, 2021 [29]	8 young adults (Anglophone); 2 channels on parietal-temporal	Filtering; ICA; Sleep spindle analysis; ERSP; Artifact detection & baseline correction; integration with SleepSMG & FieldTrip	EEGLAB integration with other toolboxes (SleepSMG & FieldTrip) is still manual
13	Niu *et al.*, 2022 [30]	30 NSZ patients, 32 ED patients, 34 healthy; 64-channel	Downsampling; filtering; ICA; artifact removal; microstate analysis; topographic clustering (A-F); calculation of coverage; occurrence; duration; scale-free dynamics analysis with Hurst exponent	Not explained
14	García *et al.*, 2022 [31]	OSF public dataset; 65-channel	Data prepocessing	Not for multivariate decoding; Does not support BIDS-EEG; Distortion-prone filter; No nested CV/blind analysis
15	Pozharliev *et al.*, [32]	112 business students; 24-channel	Filtering; ICA; Segmentation; Frontal theta spectrograms	Not explained

No	Author & Year	Dataset	Use of EEGLAB	Limitations of EEGLAB
16	Fuhrmeister *et al.* [33]	45 native German speakers; 61-channel	Filtering; ICA; eye artifacts (SASICA); channel interpolation	Not explained
17	Mushtaq *et al.* [34]	29 participants (Rapid arm-reaching task); 64-channel	Filtering; re-referencing; downsampling; ICA (Infomax); Automatic artifact rejection; Epoching & baseline correction; integration with the Fieldtrip toolbox	Not explained
18	Lopes *et al.* [35]	25 epilepsy patients (EPILEPSIAE); 19-channel; 30 healthy subjects (BASE); 60-channel	Bandpass filter; notch filter; extended Infomax ICA; time-series IC; power spectrum density (PSD); topoplot; Labeling IC	EEGLAB ICLabels do not use time-series ICs, thus reducing accuracy
19	Harwood *et al.* [36]	58 children aged 24-48 months; 128-channel	Filtering; PREP pipeline; Rereferencing; Epoching & baseline correction; ERP analysis	Not explained
20	Bi *et al.* [37]	24 surgical patients (propofol, sevoflurane, ketamine); 256-channel	Filtering; ICA; Artifact removal; Coherence Analysis (CA); Sparse Representation (SR)	Less efficient for 256-channel analysis
21	Pellegrini *et al.*, 2023 [38]	Pseudo-EEG simulation	Integration with ROIconnect for connectivity analysis and visualization of EEG data	Not explained
22	Caetano *et al.*, [39]	3 groups of healthy subjects (Resting-state (RS), Eyes Open/Closed (EO/EC), Motor Imagery (MI)); 32-channel	Artifact Removal (Gradient & Pulse Artifact); integration with AAS (Average Artifact Subtraction)	Inefficient for real-time processing
23	Bailey *et al.* [40]	127 participants (Go-Nogo ERP task); 64-channel	Filtering; ICA; epoching; ERP visualization; ICLabel; PREP; wICA; MWF	ICA (Infomax/FastICA) on EEGLAB is less effective for ERP data <1 Hz
24	Rashmi *et al.* [41]	UCI EEG Eye State dataset; Private EEG data (yoga and relaxation sessions)	EEG preprocessing; Signal visualization	Not beginner-friendly (not a simple GUI)
25	Coyle *et al.* [42]	58 participants (30 mTBI, 28 control); 64-channel	Preprocessing; Spectral power (FFT) and connectivity (wPLI) analysis	Not explained
26	Simfukwe *et al.* [43]	890 subjects (269 HC, 356 MCI, 265 AD)	FFT; ICA; ASR	Manual dominant preprocessing (e.g. ICA, ASR)
27	Jianbiao *et al.* [44]	20 subjects (10 tinnitus patients & 10 healthy subjects); 64-channel	Notch filter; ICA; re-referencing; segmentation	ICA needs manual curation; Does not support advanced non-linear analysis
28	Hbibi *et al.* [45]	22 ICU coma patients; 14-channel	ICA (AMICA algorithm); EEG Topography Plot; ICLabel / MARA; Cleanline plugin; REGICA / AAR plugin	Needs visual/manual intervention for certain artifact removal; Does not yet support full multifractal analysis.
29	Gao *et al.* [46]	20 experienced meditators and 18 lay novice meditators; 128-channel	FMRIB plugin (AAS method); ICA; FFT; STFT	Cannot be used for real-time artifact reduction; requires manual pre-processing
30	Simfukwe *et al.* [47]	534 subjects (269 HC and 265 AD); 19-channel	Bandpass filter; ICA; Epoching; Referencing; coherence analysis; PSD	Less able to describe functional coherence between brain regions
31	Zhou *et al.* [48]	50 subjects (24 migraine patients & 26 healthy controls); 16-channel	Band-pass filter; Re-referencing; AAR; EEG data segmentation	Analysis is not real-time; artifact detection remains manual
32	Wu *et al.* [49]	29 stroke patients (with and without fatigue); 64-channel	ICA; band-pass filter; segmentation; Re-referencing	Manual visual inspection; Segmentation & static noise detection; Does not support direct connectivity analysis
33	Mazzeo *et al.* [50]	99 SCD patients; 64-channel	PREP pipeline + ICA; ICLabel; Epoching & Averaging; PSD; Topographic Microstates; Data Referencing; Segmentation & Interpolation	Reliance on visual inspection; Not fully automated; Does not yet support live machine learning
34	Kawar *et al.* [51]	23 ADHD children; 32-channel	EEG Preprocessing; FFT; Electrode-specific analysis; Spectral Parameterization; Bandwidth & Aperiodic Exponents	Lack of advanced automated artifact integration
35	Knoph *et al.* [52]	37 subjects (17 CP patients with pain + 20 healthy controls; 62-channel	Filtering; Re-referencing; ICA; ICALabel; Downsampling; ERP Extraction	Visual inspection dependency; limitations of non-linear EEG analysis
36	Zhao *et al.* [53]	132 adolescents (107 MDD + 25 HC); 64-channel	Band-pass filter; ICA; Segmentation & epoching; ERP extraction; Topography and averaging	Manual and Visual ICA; Limitations of Real-time Analysis; Dominance of Linear ERP Analysis
37	Taberna *et al.* [54]	16 subjects (Resting state, visual attention task, motor execution task); 128-256 channels	Bandpass filter; BSS; ICA; ERP analysis	Less suitable for large datasets; Manual visualization & inspection; Artifact removal not fully automated
38	Cannard *et al.* [55]	1 subject (NEMAR platform); 63-channel	Filtering; re-referencing; ICA; ASR; BrainBeats Plugin; Entropy & Complexity Estimation	Does not support combined EEG-ECG/PPG analysis; Does not automatically remove cardiac artifacts
39	Kalburgi *et al.* [56]	34 participants (Resting-state EEG: eyes open & eyes closed)	EEG Preprocessing; Microstate map identification; Backfitting; Topography	Not explained
40	Mondellini *et al.* [57]	27 healthy participants (Resting-state and cognitive tasks); 30-channel	Bandpass Filter; ASR; ICA; ICLabel; Rereferencing; Spectral Analysis; MWL Index Calculation	EEGLAB does not cover non-linear features or brain connectivity
41	Hsieh *et al.* [58]	58 students (Flanker Task); 64-channel	High-pass filter; extended-infomax ICA; artifact rejection; Eyeblink detection; Morlet wavelet transform; ROI	Reliance on manual ICA; Reliance on manual configuration; No validation of non-ocular artifacts
42	Niedernhuber *et al.* [59]	1 subject; 7-channel	EEG preprocessing; semi-automatic artifact rejection; Hilbert transform; power spectral analysis	Does not support automatic TET integration
43	Vourvopoulos *et al.* [60]	4 chronic stroke patients (motor imagery (MI) + motor observation (MO) in VR); 32-channel	Downsampling; bandpass filter; channel interpolation; re-referencing; ASR; ICA; Epoching & Segmentation; ERSP	Does not support direct multimodal EEG-fMRI
44	Simfukwe *et al.* [61]	890 subjects (269 HC, 356 MCI, 265 AD); 19-channel	Filtering; ASR; ICA; Relative PSD	Artifacts not yet fully eliminated automatically; Not yet integrative multimodality
45	Niforatos *et al.* [62]	34 healthy participants; 3-channel (BCIglass); 20-channel (Enobio 20)	High-pass & notch filtering; Re-referencing; Bad channel rejection; Channel interpolation; ICA; ICLabel plugin; Epoching; Time-frequency decomposition; Welch's PSD	High manuality in ICA; Does not support direct HMD integration; Limited to real-time applications

No	Author & Year	Dataset	Use of EEGLAB	Limitations of EEGLAB
46	Pasqualette *et al.* [63]	74 participants; 32-channel	Bandpass Filtering; CleanLine (PREP pipeline); ICA (Infomax); Epoched Data; Re-referencing; Automatic Artifact Rejection; ERP Component Analysis	Need additional integration for eye-tracking; Artifact rejection not entirely automatic
47	Miras *et al.* [64]	18 (TMS-EEG) & 31 (resting-state EEG)	EEG preprocessing; Source modeling pipeline	Does not support FD analysis directly; requires additional software for source modeling
48	Kumari *et al.* [65]	10 subacute spinal cord injury (SCI) patients; 64-channel	EEG Preprocessing; ERSP Analysis; Frequency Band Analysis	Preprocessing is not fully automated; Does not support real-time FES integration
49	Zur *et al.* [66]	31 healthy participants; 64-channel	ICA; ICLabel; CleanRawData; interpolation; baseline; Mu-Rhythm & Theta power; ERSP via Morlet wavelet; dipole fitting via DIPFIT	Manual dependent preprocessing; Need external plugin for ICA labeling; Artifact detection not fully automated
50	Zhang *et al.* [67]	103 OSA patients (27 mild, 30 moderate, 46 severe); 6-channel	Bandpass Filtering; ICA; Threshold Artifact Manual; Hilbert Transform; EEGfilt Function	Manual and semi-automated preprocessing; Does not support full PSG-EEG integration
51	Kim *et al.* [68]	199 participants (75 IGD, 57 AUD, 67 HC); 64-channel	CleanLine plugin; bandpass filtering; artifact subspace reconstruction; wavelet denoising; ICA + ICLabel plugin; Epoching & artifact thresholding	Need for external plugins for microstate; Artifact detection not fully automated
52	Chen *et al.* [69]	52 migraine patients & 34 healthy controls; 64-channel	Bandpass filter; baseline correction; ICA; PSD; ERP	ICA needs manual confirmation; Lack of non-linear analysis integration; Pipeline not fully automated
53	Wojtecki *et al.* [70]	10 Alzheimer's patients; 21-channel	Filtering; Average referencing; Data segmentation; Spectral analysis (FFT); Tsallis Entropy analysis	Artifacts are removed semi-automatically; Does not yet support multimodal biomarker estimation
54	Li *et al.* [71]	43 participants (22 long-term Baduanjin + 21 short-term); 32-channel	Band-pass filtering; Re-referencing; Epoching; FFT transform; Frontal Alpha Asymmetry (FAA) Analysis	Artifact cleaning is semi-automated
55	Korochkina *et al.* [72]	32 subjects (semantic priming task); 64-channel	Filtering; re-referencing; Epoching; ICA; ERP Analysis	Does not support advanced analysis such as connectivity mapping in semantic integration

IV. Discussion

A. Preprocessing Features of EEGLAB

EEGLAB provides a complete and effective set of preprocessing features to prepare EEG data before further analysis, as shown in Fig. 4. The first step in preprocessing generally starts with a filtering stage to remove distracting noise and artefacts [73]. EEGLAB has a variety of filter options, including a high-pass filter to eliminate low-frequency components such as drift, a low-pass filter to reduce muscle noise that appears in high frequencies, a band-pass filter to preserve the signal in the relevant frequency range, and a notch filter that is specifically used to remove electrical noise at 50 or 60 Hz [74]. After the filtering stage, a re-referencing step is performed to determine the appropriate reference for a more accurate interpretation of the EEG data [75]. EEGLAB provides several re-referencing options, including average referencing which uses the average activity of all electrodes, linked-mastoid referencing which utilises the mastoid electrodes behind the ear, and custom referencing which allows researchers to select specific electrodes as references according to research needs [76].

To improve data quality, EEGLAB provides comprehensive artifact rejection features, both manually and automatically. In the manual approach, researchers can visually inspect the EEG data and mark contaminated epochs [77]. Automatically, EEGLAB is able to detect artefacts based on parameters such as threshold amplitude and abnormal kurtosis [78]. The artifact subspace reconstruction (ASR) plugin is also available as an advanced solution to remove large artefacts such as body motion or heavy electromagnetic interference, by reconstructing the EEG signal from an artefact-free subspace [79]. Furthermore, the bad channel detection and interpolation feature allows users to identify problematic electrodes-for example due to excessive noise or poor electrode contact-and correct them through interpolation of neighbouring electrodes with the spherical interpolation method [80]. EEGLAB also supports down sampling or resampling to lower the sampling frequency of EEG data from high to lower, in order to reduce the computational burden without sacrificing signal quality [81].

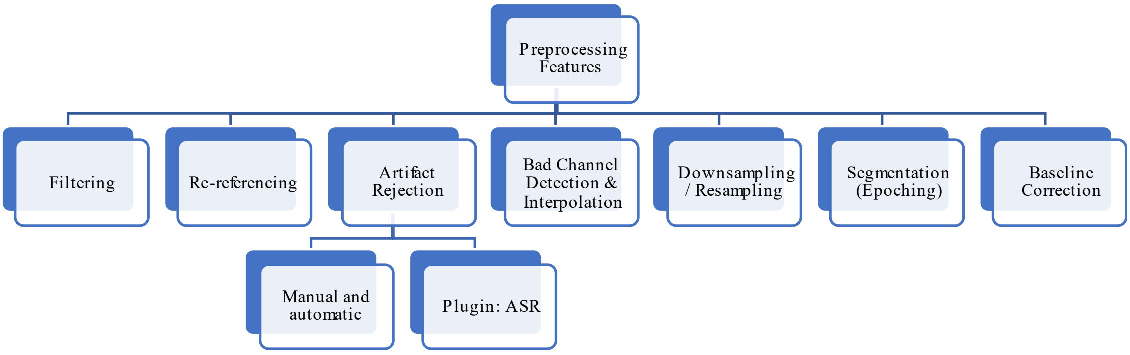

Fig. 4. Preprocessing features of EEGLAB

The next stage is segmentation or epoching, which is the cutting of continuous EEG data into short segments based on a specific event or stimulus, which is important for analyses such as event-related potentials (ERP) [82]. Each of these epochs then undergoes baseline correction, which is the process of subtracting the average EEG activity from the baseline period before the stimulus, so that the EEG response obtained truly reflects the stimulus-related activity accurately, rather than being the result of signal fluctuations or baseline drift [83]. With this set of preprocessing features, EEGLAB is able to effectively improve the quality of EEG signals, making the data ready for advanced analyses such as spectral analysis, functional connectivity, or brain activity source estimation [84]. This makes EEGLAB an essential toolbox in EEG research that is flexible, efficient, and reliable.

B. *Independent Component Analysis (ICA)*

The independent component analysis (ICA) feature in EEGLAB is one of the main advantages of this toolbox that enables in-depth analysis of EEG data by separating the signal into independent components [85]. ICA effectively separates the original EEG activity from artefacts that often appear in EEG recordings such as ocular artifacts, muscle artifacts, heart rate artefacts and other noise. The ICA process works by assuming that the measured EEG data is a linear mixture of several mutually independent activity sources, then the ICA algorithm separates these sources so that users can selectively identify and remove artefact sources without losing important information from the actual brain activity.

Furthermore, EEGLAB provides a complementary feature in the form of ICLabel plugin that further enhances the effectiveness and efficiency of ICA. ICLabel uses a machine learning approach to automatically classify ICA components into specific categories such as brain (brain activity), muscle (muscle artefacts), eye (eye blink or eye movement artefacts), heart (heart rate artefacts), line noise (noise from the power grid), channel noise (bad channel-related artefacts), and other (categories that do not fit into these classifications) [86]. With this automatic classification, ICLabel simplifies the process of identifying components containing artefacts, while reducing reliance on subjective and time-consuming manual inspection. EEGLAB users can immediately decide which components should be discarded based on the classification probabilities provided by the plugin, thus improving the accuracy and speed of EEG data preprocessing [85].

EEGLAB also presents an advanced feature known as Dipole Fitting through the DIPFIT plugin. This feature aims to estimate the location of the source of brain activity from the independent components that have been generated by ICA. Using realistic or standard head models available in EEGLAB, DIPFIT calculates the most appropriate dipole (electrical activity source) position for each independent component [86]. This dipole location information is very useful for studies that require spatial analysis of brain activity sources, such as cognitive and neuroclinical studies that want to know precisely which brain areas are involved in a particular mental process or disease [87].

These three ICA features in EEGLAB (basic ICA processing, ICLabel for automatic classification, and DIPFIT for brain activity source location estimation) together provide an integrated solution for preprocessing and analysis of complex EEG data [88]. Thus, EEGLAB is not only able to effectively clean EEG data from artefacts, but also provide additional insights into the spatial origins of brain activity that are more detailed, in-depth and scientifically and clinically meaningful [89].

C. *EEG Data Analysis*

EEGLAB provides a variety of powerful and flexible EEG data analysis features to explore various aspects of brain activity, one of which is time-frequency analysis, as shown in Fig. 5. In this feature, EEGLAB offers approaches such as short-time Fourier transform (STFT) and wavelet transform [90]. STFT allows simultaneous analysis of EEG spectral dynamics in the time and frequency domains by breaking the EEG signal into small segments that are analyzed independently [91]. Wavelet transform, on the other hand, is a more flexible method as it is able to adjust the time-frequency resolution depending on the frequency being analyzed, which is ideal for capturing transient activity or brief changes in brain activity that are not obvious using traditional frequency methods [92]. The combination of these two techniques in EEGLAB enables in-depth analysis of EEG frequency changes that are closely related to cognitive processes as well as specific pathological conditions.

In addition to spectral analysis, EEGLAB is also widely known for its ability to analyze Event-Related Potentials (ERP). ERP is an EEG response obtained by averaging EEG segments to a certain stimulus or event. EEGLAB provides full features for preprocessing, epoching, averaging, as well as visualization of ERPs that allow researchers to clearly see specific EEG components such as N100, P300, or N400 associated with cognitive functions such as attention, memory, and language processing [93].

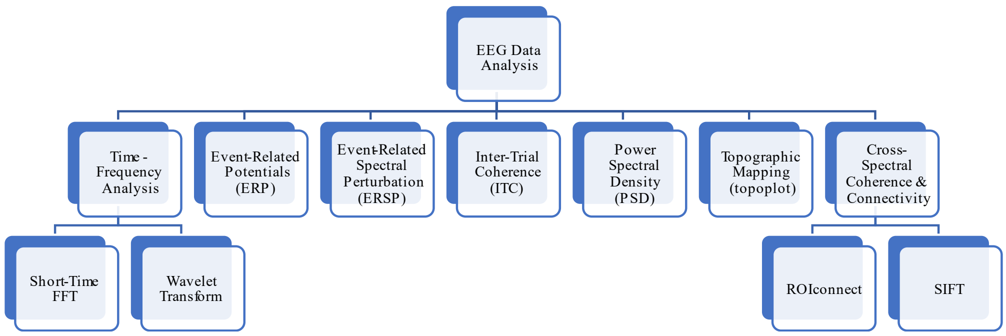

Fig. 5. EEG data analysis

In addition to ERP, EEGLAB also offers the event-related spectral perturbation (ERSP) analysis feature. ERSP is an advanced analysis that explores changes in EEG spectral power within a certain time after a stimulus, allowing users to see more complex dynamics of brain activity, including increases (event-related synchronization, ERS) and decreases in power (event-related desynchronization, ERD) at certain frequencies [94].

Another important feature is inter-trial coherence (ITC), which evaluates the phase consistency of EEG activity to a stimulus across multiple trials. ITC is very useful in understanding the synchronization of neural activity at the neuronal level associated with stimulus processing or certain cognitive processes [95]. ITC allows EEGLAB users to evaluate whether EEG activity at a particular frequency consistently appears at the same time after a stimulus, which is a strong indicator of an organized brain response to a particular stimulus [96].

Power spectral density (PSD) is also a widely used EEG analysis feature in EEGLAB. PSD provides a complete picture of the power distribution of the EEG signal at various frequencies, helping to identify different patterns of activity between specific conditions or groups of subjects [97]. PSD is also often used to assess certain clinical conditions, such as epilepsy or sleep disorders, which exhibit distinctive EEG spectral activity patterns at specific frequencies. Complementing the PSD feature, EEGLAB provides powerful spatial visualization capabilities through topographic mapping (topoplot) [98]. Topoplot allows users to visualize the spatial distribution of EEG activity across the surface of the head in an intuitive and informative manner. This visualization is critical to understanding where exactly specific brain activity is occurring, thus facilitating the interpretation of EEG research results [99].

Finally, EEGLAB also provides advanced features for brain connectivity analysis through additional plugins such as ROIconnect and source information flow toolbox (SIFT). The cross-spectral coherence and connectivity analysis features allow users to explore the functional relationships between different brain regions based on EEG signals [100]. Using ROIconnect, researchers can evaluate interactions between different brain regions, while the SIFT plugin is able to provide more sophisticated analysis of the direction of information flow between brain regions (directional connectivity), such as Granger causality. Thus, the EEG data analysis features in EEGLAB not only facilitate the interpretation of local brain activity, but also provide deep insights into how these regions dynamically interact within the overall brain network [101].

D. Advanced Analysis & Plugin Support on EEGLAB

EEGLAB provides a variety of advanced analysis features supported by an extensive plugin system, one of which is microstate analysis. Microstate analysis, accessible through the Microstate plugin in EEGLAB, allows researchers to evaluate the temporal patterns underlying the dynamics of resting-state EEG activity. Microstates are often referred to as “cognitive atoms”, where global EEG activity can be grouped into a small number of topographic patterns that are stable over short periods of time, typically tens to hundreds of milliseconds [102]. EEGLAB provides tools to automatically extract microstates from EEG data, calculating metrics such as duration, frequency of occurrence, coverage, and transitions between microstates. Microstate analysis is very useful in exploring normal brain function as well as changes in neuropsychiatric conditions such as depression, schizophrenia, or dementia [103].

In terms of efficient and standardized EEG artifact cleaning, EEGLAB provides a comprehensive pipeline through several advanced plugins. One of the most popular pipelines is the PREP Pipeline, which offers a systematic and standardized preprocessing approach, including robust re-referencing, bad channel detection, channel interpolation, and filtering [104]. This pipeline is essential in ensuring consistency between subjects and EEG recording sessions, making the EEG analysis results more reliable. Another very important plugin in artifact cleaning is CleanLine, which effectively removes line noise artifacts from 50 or 60 Hz power grids without damaging the original EEG signal. CleanLine uses a regression-based adaptive approach so as to maintain the integrity of the original EEG data [105].

In addition, EEGLAB provides specialized plugins such as multiple artifact rejection algorithm (MARA), ADJUST, and semi-automatic selection of independent components for artifact correction (SASICA), which are used in the context of ICA analysis to aid automatic identification of artifact components that are difficult to detect manually [106]. MARA uses machine learning to automatically classify artifact components with a high degree of accuracy, while ADJUST specifically focuses on ocular artifacts and eye movements, and SASICA provides a semi-automated approach that helps users evaluate ICA components visually and quantitatively [107].

With this combination of plugins, EEGLAB users can manage artifacts more accurately, efficiently, and objectively. Artifact subspace reconstruction (ASR) is one of EEGLAB's flagship features specifically designed to automatically address heavy artifacts, such as head movements or other large technical artifacts [108]. ASR works by detecting and replacing damaged or artifact-contaminated EEG signal segments using stable and clean EEG data subspaces. This method is very effective in dealing with large, spontaneous artifacts that are difficult to overcome with traditional cleaning methods, making it particularly suitable for use on EEG data recorded in naturalistic or free-motion situations [109].

EEGLAB also provides limited features for multimodal integration, which allows users to combine EEG data with other modalities such as fMRI or physiological signals such as photoplethysmography (PPG) [110]. This integration is done through an additional plugin that enables synchronization and combined analysis between modalities [111]. Although this multimodal integration feature is limited and requires additional configuration, EEGLAB remains a good choice for researchers who want to perform combined analysis of EEG with neuroimaging data or other physiological data, especially in studies that require cross-validation between modalities [112]. The following are some other features of the advanced analysis & plugin support in EEGLAB, as shown in Table III.

TABLE III. FEATURES OF ADVANCED ANALYSIS & PLUGIN SUPPORT IN EEGLAB

Features / Plugins	Description	Key Benefits
SIFT (Source Information Flow Toolbox) [113]	Plugins for dynamic connectivity analysis between brain sources using Granger Causality, PDC.	Reveals the direction and strength of information flow between brain areas. Suitable for neurodynamic studies.
ROIconnect [114]	Plugin for connectivity analysis between Regions of Interest (ROI) in source-reconstructed EEG data.	Provides region-specific functional connectivity mapping of the brain.
DIPFIT (Dipole Fitting Plugin) [115]	Plugin to map ICA components to brain sources with dipole location estimation.	Provides spatial information from EEG signals for localization studies of brain activity.
ICLabel [116]	Machine learning plugin for automatic classification of ICA components into categories (Brain, Eye, and Muscle).	Assists in quick and accurate selection and cleaning of ICA components.
NFT (Neuroelectromagnetic Forward Head Modeling Toolbox) [117]	Plugin for creating realistic head models from MRI data or templates.	Improves source localization accuracy with a personalized head model.
ERPLAB [118]	EEGLAB companion toolkit for Event-Related Potentials (ERP) analysis.	Provides ERP-specific workflows such as averaging, binning, and measurement window.
BCILAB [119]	Toolkit for building and evaluating EEG-based Brain-Computer Interface pipelines.	Supports real-time classification and interactive BCI applications.
FIRfilt [120]	Additional plugins for filtering EEG signals using high-precision Finite Impulse Response (FIR).	Provides better control over EEG filter characteristics.
FieldTrip Integration [121]	EEGLAB can be integrated with the FieldTrip toolbox for advanced analysis and nonparametric statistics.	Extends the functionality of EEGLAB into the realm of advanced statistics and frequency analysis.
MoBILAB [122]	Plugin for mobile EEG analysis including motion detection and IMU integration.	Useful for real-world or naturalistic EEG experiments.

Finally, EEGLAB provides support for modern standard data formats through an additional plugin called bids-MATLAB-tools, which supports the brain imaging data structure for EEG (BIDS-EEG) format. This format is designed to facilitate the storage, management, and sharing of EEG data in a systematic, open, and standardized manner. With the support of BIDS, EEGLAB is able to improve the interoperability and reproducibility of EEG data between laboratories and research platforms, helping the EEG community to implement open science principles more easily and efficiently [123].

E. *Interface and Extensions*

EEGLAB is a popular MATLAB-based EEG analysis software, in part because it has an intuitive and user-friendly graphical user interface (GUI). EEGLAB's GUI is designed to make it easy for users of various skill levels, ranging from beginners to advanced users, to perform EEG analysis without having to have in-depth expertise in MATLAB programming [124]. Through its GUI, EEGLAB presents various important features such as preprocessing, filtering, independent component analysis (ICA), EEG data visualization, segmentation, to advanced analysis such as ERSP and top plot, in a clear and structured menu and button format. With this point-and-click approach, users can easily access, run, and monitor each stage of the analysis transparently, as well as explore the data visually and interactively, significantly reducing the risk of errors and improving analysis efficiency [125].

In addition to its GUI, EEGLAB offers full support for scripting through the MATLAB programming language. This scripting feature allows users who have more complex analysis needs and high customization to perform automated and batch processing of EEG data. By using scripting, users can efficiently run repetitive analysis on large datasets without significant manual intervention, improving the consistency and reproducibility of analysis results [126]. EEGLAB provides clear and extensive documentation on the MATLAB commands associated with each of its GUI features, making it easy for users to integrate EEGLAB scripts into their automated workflows, such as batch analysis for large experiments or multi-center collaborative projects [127].

One of EEGLAB's key advantages is its extensive and growing plugin system, supported by an active global community. To date, there are hundreds of additional plugins developed by EEGLAB's extensive user community, covering a wide range of advanced analyses, such as brain functional connectivity, microstate analysis, multimodal integration, machine learning classification, and EEG source analysis [128]. Plugins such as ICLabel, DIPFIT, MARA, SIFT, CleanLine, ROIconnect and others extend EEGLAB's analytic capabilities far beyond its basic features, allowing users to access the latest methodologies in EEG research without the need to develop their own algorithms. EEGLAB's plugin system is also well designed so that users can easily add or remove plugins according to their needs via the GUI or programmatically via MATLAB scripting [129].

Finally, EEGLAB offers flexibility in terms of importing and exporting EEG data, supporting various common data formats that are widely used in the international EEG community. The main format of EEGLAB itself is *.set, which includes a complete data structure with information about the EEG data, electrode locations, event markers, and analysis results [130]. EEGLAB also provides extensive support for other formats such as European Data Format (EDF), BioSemi Data Format (BDF), Comma-Separated Values (CSV), and MATLAB's *.mat format. Support for these formats allows EEGLAB users to easily integrate with other EEG software, share data with collaborators from various institutions, and maintain compatibility with different EEG acquisition systems [131]. Thus, the combination of an intuitive GUI, MATLAB scripting for automation, extensive system plugins, and extensive data import/export capabilities make EEGLAB a highly flexible, effective, and user-friendly software for modern EEG analysis [132].

V. Prospects and Limitations

A. Prospects of EEGLAB in EEG Signal Processing

EEGLAB is a software that has bright prospects in EEG signal processing, especially due to the growing needs of neuroscience, neurotechnology, and clinical research. The main prospect of EEGLAB in EEG processing lies in its ability to provide a flexible and constantly evolving analysis platform, especially thanks to the support of an extensive and active open-source community. This community support allows EEGLAB to continue to receive regular updates, introduce the latest analysis methods, and support the needs of users in various research fields that require complex EEG analysis, such as neuromodulation, neurofeedback, brain-computer interface (BCI), and neuropsychiatric and neurodegenerative research [133].

In the field of cognitive neuroscience, EEGLAB is particularly promising as it offers a wide range of advanced analysis techniques that are constantly evolving. Techniques such as independent component analysis (ICA), event-related spectral perturbation (ERSP), microstate analysis, and functional connectivity analysis provide deep insights into the basic mechanisms of the brain [134]. With the integration of additional plugins such as DIPFIT and SIFT, EEGLAB enables accurate spatial source analysis as well as brain network connectivity evaluation, helping researchers explore neuronal activity at a more detailed and realistic level. In the future, EEGLAB is predicted to continue adopting more advanced analysis approaches such as dynamic modeling, integration of machine learning for EEG pattern classification, as well as complex brain network analysis that is increasingly required by the scientific community [135].

In the clinical context, EEGLAB has strong prospects to support the diagnosis and monitoring of various neurological and neuropsychiatric conditions. EEGLAB's ability to separate artifacts with advanced methods such as artifact subspace reconstruction (ASR) and automated ICA such as ICLabel enables the resulting clinical EEG data to be of high quality, artifact-free, and ready for more accurate clinical interpretation [136]. Going forward, the integration of EEGLAB with machine learning and artificial intelligence (AI) technologies for automatic classification of pathological conditions, such as epilepsy, depression, dementia, or ADHD, will further expand, improving the efficiency of EEG-based diagnostics. In addition, additional plugins that support multimodal signal analysis such as the integration of EEG-fMRI, EEG-NIRS, or EEG with other physiological data will further expand the utility of EEGLAB in modern clinical applications [137].

Another important prospect for EEGLAB is the expansion of EEG big data analysis capabilities. With the increasing popularity of EEG studies with large numbers of subjects or longitudinal collection of EEG data, EEGLAB is predicted to further increase support for automated, standardized, and reproducible large-scale data analysis [138]. Support for standardized formats such as brain imaging data structure (BIDS-EEG) strengthens EEGLAB's position in the open science and big data community, enabling more efficient international collaboration and easier exchange of EEG data across institutions. EEGLAB is also expected to continue developing more intuitive MATLAB-based interfaces and scripting to improve the efficiency and automation of large batch analysis, making it a flagship platform for future global EEG research [139].

In addition, EEGLAB's prospects in the field of EEG wearable technology and brain-computer interface (BCI) are also very promising. EEGLAB is predicted to further develop towards better compatibility and integration with portable and real-time EEG devices, which are currently in increasing demand both in the context of research and clinical applications [140]. The development of features for real-time EEG processing and direct integration with head-mounted displays (HMDs), virtual reality (VR), augmented reality (AR), and neurofeedback systems will open up many new opportunities in neurological rehabilitation, cognitive training, or neuroergonomic applications [141].

Thus, EEGLAB's prospects in EEG signal processing are very bright, supported by a combination of technological innovation, analysis flexibility, community support, integration of the latest analytical methods, as well as commitment to open science standards and interoperability of EEG data. EEGLAB is predicted to remain the software of choice in EEG analysis across a wide range of disciplines, from basic neuroscience to clinical applications and advanced technologies, in the future.

B. Limitations of EEGLAB in EEG Signal Processing

While EEGLAB is a powerful, flexible and popular EEG analysis software, there are some limitations that users need to understand in the context of EEG signal processing. One of the main limitations of EEGLAB is the still significant reliance on manual and semi-automated processes in some preprocessing stages, particularly in artifact detection and removal [142]. While plugins such as ICLabel, ASR, ADJUST and MARA have been developed to automate most of these processes, EEGLAB still requires manual visual inspection and verification by the user in most cases. This increases the risk of subjectivity, inconsistency between users, and adds to the time and effort required, especially in large EEG datasets or in studies with many subjects [143].

Another limitation of EEGLAB lies in the spatial source modeling-based analysis. Although the DIPFIT plugin provides source location estimation of brain activity, the spatial resolution provided by EEG is inherently low when compared to other brain imaging methods such as fMRI or MEG [144]. In addition, dipole fitting in EEGLAB relies heavily on the provided head model and may not be optimal if the standardized head model is less accurate for a particular subject. This could potentially lead to inaccuracies in EEG activity source location estimation, especially in the case of studies that require high spatial resolution or highly precise activity source localization [145].

EEGLAB also has limitations in terms of multimodal data integration. While several external plugins are available for integration with other modalities such as fMRI, NIRS, or additional physiological signals (ECG, PPG), these integrations are not native and are generally still limited in both flexibility and efficiency. Additional configurations are often complex and require advanced technical knowledge from the user, which may hinder novice users or users from clinical fields who do not have a strong technical background [146]. In addition, real-time integration features for applications such as brain-computer interface (BCI) and neurofeedback in EEGLAB are still limited, reducing its potential in real-time and interactive usage scenarios.

Another important limitation is related to the computational efficiency and scalability of EEGLAB in the face of large-scale or high-density EEG data analysis [147]. Analysis processes such as ICA, time-frequency analysis, and dipole fitting can be time-consuming and demand large computational resources, especially if the dataset is very large or consists of many subjects [148]. EEGLAB, being MATLAB-based, is inherently not as optimized as other platforms that use faster programming languages such as Python, which naturally favor parallel processing or effective use of GPUs. This can be a significant bottleneck when researchers need to analyze large-scale EEG data efficiently and quickly [149].

Lastly, while EEGLAB has an intuitive GUI for general use, some users especially novices still face challenges related to the high learning curve for advanced analysis features such as brain network connectivity analysis, microstate, or machine learning integration. The EEGLAB documentation, although extensive, is often complex and not always easy to understand for new users without a strong MATLAB or EEG background [150]. This leads to the need for intensive training and additional support for users who want to fully utilize EEGLAB's advanced capabilities, especially when users want to perform complex specific analyses or apply the latest analysis approaches that require the integration of additional plugins [151].

Thus, while EEGLAB has many advantages and broad potential, these limitations indicate that users need to consider technical, computational, and practical aspects when choosing EEGLAB as the primary tool for their EEG analysis. Understanding these limitations is important so that users can appropriately design the optimal analysis approach, know when to complement EEGLAB with additional tools or analysis methods, or even choose other software more specific to their EEG research or application needs.

VI. CONCLUSION

A review of recent literature indicates that EEGLAB remains one of the most widely adopted and effective tools for EEG signal analysis. Studies published between 2020 and 2024 highlight its extensive application in both basic preprocessing steps (such as filtering, ICA, and re-referencing) and in advanced analytical techniques, including time-frequency analysis, ERSP, ERP, PSD, microstate analysis, and brain connectivity mapping. EEGLAB’s key advantages lie in its analytical flexibility, offered through a user-friendly graphical interface, a MATLAB-based scripting environment that facilitates process automation, and a comprehensive plugin architecture that continues to evolve, supported by an active and collaborative international user base.

In terms of prospects, EEGLAB has very promising potential in supporting cross-disciplinary EEG research, ranging from cognitive neuroscience to clinical applications and the development of EEG wearable technology and brain-computer interface (BCI). EEGLAB is projected to further develop through the integration of the latest analysis methods, such as machine learning and multimodal analysis, and further strengthen its support for big data-based EEG analysis. Support for standardized data formats such as BIDS-EEG and the development of additional plugins for the integration of other modalities (such as fMRI, NIRS, and physiological data) are expected to increase the flexibility and interoperability of EEGLAB in the future.

However, there are some significant limitations that need to be addressed in the use of EEGLAB. The high reliance on manual or semi-automated processes, especially in artifact detection and removal, is a major challenge when dealing with large or complex datasets. The limited spatial resolution in dipole fitting features also hinders EEG analysis that requires high precision in the localization of brain activity sources. In addition, although EEGLAB has a multimodal integration plugin, its implementation is not yet native and is often complex, adding a level of technical difficulty for less experienced users.

Computationally, the efficiency of EEGLAB is limited, especially in large-scale EEG analysis, requiring high computational resources and relatively long processing times compared to some other programming language-based EEG analysis platforms, such as Python. This challenge is further compounded by the high learning curve for new users, especially in understanding advanced features and complex plugin integration, requiring additional training or intensive mentoring.

Overall, EEGLAB remains the flagship software in EEG analysis due to its feature set, flexibility, and extensive community support. However, to maximize its potential in the future, the development of EEGLAB should be directed towards improving automation and computational efficiency, more seamless multimodal integration, and increasing the spatial and temporal resolution of analysis. Understanding the strengths and limitations of EEGLAB is very important so that users can make the right decision in choosing an EEG analysis method that suits their research needs and clinical applications.

VII. SUGGESTIONS FOR FUTURE RESEARCH

Based on the findings from the reviewed studies on EEGLAB usage, several directions can be proposed to enhance future EEG research. One key recommendation is to focus on advancing automated EEG preprocessing methods that are not only more accurate but also objective and efficient. This can be achieved by leveraging artificial intelligence (AI) and machine learning to enable high-precision detection and removal of artifacts, which in turn would reduce dependence on manual visual inspection that is often time-consuming and prone to subjectivity. Additionally, it is important to broaden the validation of these automated techniques across various subject groups and experimental EEG conditions to ensure their robustness and applicability in large-scale and heterogeneous research contexts.

Second, it is recommended that future research focus more on integrating EEG data with other neuroimaging or physiological modalities more effectively and seamlessly. Further research is needed to develop EEGLAB plugins or extensions that can easily combine EEG data with fMRI, NIRS, MEG, or additional physiological data such as ECG or PPG. With better multimodal integration, researchers can enrich the interpretation of EEG data with additional insights from other modalities, which will ultimately improve the validity and accuracy of research findings in explaining the underlying mechanisms of the brain or certain clinical conditions.

Third, future research also needs to pay attention to improving spatial resolution in EEG source analysis. This can be done by developing or integrating more accurate and personalized realistic head models, for example with the help of individual MRI or other advanced source imaging methods, so that the estimation of the location of the EEG activity source becomes more precise. In addition, cross-validation between EEG source estimation and other neuroimaging methods such as fMRI or MEG is also recommended, to ensure high reliability of EEG source analysis performed using EEGLAB.

Fourth, future research is expected to further strengthen EEGLAB's capacity in managing and analyzing large-scale EEG datasets. This includes further development in EEG big data analysis, especially through increasing EEGLAB's computing capacity based on cloud computing or GPU to reduce long analysis times. The development of MATLAB-based parallel processing algorithms or the integration of EEGLAB with Python-based EEG analysis platforms could also be an interesting solution, to address the increasing computational challenges in large-scale EEG research in the future.

Finally, future research is recommended to apply more open science principles, especially through the use of standardized EEG data formats such as BIDS-EEG. With standardized data formats, the exchange and collaboration of EEG data between researchers and institutions will be easier, increasing the transparency, reproducibility, and validity of EEG research globally. This also encourages the EEG community to share data, analysis methods, and research findings more openly, which will ultimately accelerate progress in EEG research across various scientific fields.

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