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Electroencephalography on Controlling Assistive Device: A Systematic Literature Review

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A B S T R A C T

The present article delves into the practical applications of electroencephalography (EEG) in assistive devices. The article thoroughly summarizes the current state of the art, research trends, methods, and implementation. The focus is primarily on how EEG can operate various assistive devices effectively, incorporating artificial intelligence, machine learning, and several computing methods. The authors emphasize the importance of conducting more research and development in the field and offer valuable insights into its prospective directions. A complete search of the Scopus database from 2017 to 2022, including journals and proceedings such as IEEE Xplore, MDPI, Springer, Frontiers, and ScienceDirect, was conducted to ensure the findings are as comprehensive as possible. Conferring to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, 4397 metadata were transformed into 45. Based on the data synthesis, the following study execution must prioritize determining whether the observed signals are attributable to EEG artifacts or actual EEG signals. The derivation of input signals for controlling helpful devices can be enhanced by utilizing familiar activities, such as facial muscle movements, and employing various machine-learning techniques to ensure high levels of accuracy.

INTRODUCTION

A systematic literature review requires thorough and methodical research [1] on Electroencephalography (EEG) implementation in assistive devices. This evaluation will include a thorough search for relevant papers, an assessment of their methodological rigour and overall quality [2], and then a synthesis of the results to give a complete picture of the current state of knowledge [3] about how EEG can be used in medical engineering to make devices that help people. Researchers can identify knowledge deficits and recommend future research by conducting a systematic review.

The purpose of the evaluation that has been proposed is to conduct an in-depth analysis of a variety of scholarly works that were produced between the years 2017 and December 2022. These works include conference proceedings, scholarly articles, technical reports, and other pertinent sources. The inquiry would involve a comprehensive review of the datasets stored within the Scopus database, which would include looking at information from various sources, including the IEEE Xplore, MDPI, Springer, Frontiers, and ScienceDirect, amongst others.
This review aims to appraise the standard of electroencephalography (EEG) research concerning the regulation of assistive equipment, particularly in medical engineering. The evaluation will be based on pre-established criteria, including implementation, techniques, and themes about EEG. The assessment outcomes will be articulated lucidly and straightforwardly, focusing on the most significant findings and their implications for practical use and further investigation.

EEG is a popular neuroimaging method for numerous reasons. These features include the mobility of the EEG acquisition apparatus, its low cost, its noninvasiveness, and its excellent temporal resolution [4], [5]. EEG works in two ways [5]: non-invasive and invasive. A non-invasive is low-cost and safe because it has no risk of surgical operation [7]. It helps to monitor patients with epilepsy, stroke, or a disability [8] and even increase their level of self-reliance [8], [9]. EEG focuses on improving the quality of life for those with impairments. It can be done by optimizing the method to process the signal [10], [11], [12]

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upgrading sensors used in the study [13], improving system reliability [14], and input used [15], [16], [17], [18], [19].

Numerous researchers have implemented EEG by using NeuroScan [20], NeuroSky [21], EMOTIV [22], OpenBCI [23], BioSemi [24], and Brain Products [25] Some proposed their own system [26]. Based on the name listed, NeuroScan, the oldest company, is the most widely used EEG hardware manufacturer and has been involved in over 15800 research studies [27], followed by BrainProducts with 15000 publications [28] by July 7, 2023.

Despite the considerable progress made in the size and functionality of EEG hardware, the effectiveness and reliability of this technology remain dependent on the use of metallic sensors placed on the scalp and the application of conductive substances like gels to adjust impedances for recording brain signals. Standard EEG electrodes are built from silver (Ag) and silver chloride (AgCl) [29] and crafted in the configuration of a cup, a platter, or a thread. Given that Ag is a moderately viscous salt, AgCl swiftly becomes saturated and hits a stability point. Consequently, Ag is an outstanding option for metallic epidermal electrodes [30]. These manual tasks require EEG recording technicians. The test subject's displeasure is also noteworthy. However harmless, the electrolyte paste and abrasive gel are sticky, leaving hair and scalp moist and unclean. Adapting the impedance can take time [30]. A substantial electrolyte that accelerates impedance adaptation may generate electrical links between electrodes, which is detrimental [31]. Finally, gel drying degrades conductive characteristics when acceptable impedances are achieved. Dry electrode systems can reduce many of these issues [32]; hence, EEG dry electrode research began in the 1990s [33] and is flourishing. Practical dry electrodes were one of two disruptive breakthroughs in BCI research a few years ago [34], [35].

Increasing awareness of the importance of disability independence has led to an increase in BCI-EEG use [36], resulting in the emergence of BCI-EEG-based assistive devices. These assistive devices include electric wheelchairs [37], robot arms [38], [39], prosthetic limbs [40], virtual keyboards [41], controls for household appliances [42], and hearing aids [43]. This research topic is quite promising, as these assistive devices have been continuously developed with various input variations and control modes up until now.

Existing assistive devices can be controlled using a variety of input modalities, such as evoked or natural EEG. Steady-state visually Evoked Potentials (SSVEPs) [44], neural responses in the brain that are elicited by a visual input exhibiting a consistent flashing frequency [45], and P300, which is an endogenous event-related potential (ERP) produced by uncommon and significant catalysts in the occipital, temporal, and frontal lobes but being stored inside the parietal lobe [46], are examples of evoked EEG. Simultaneously, spontaneous EEG is a signal produced by incidental activities such as mind wandering, which consumes less energy than other nerve processes such as eye blinking and motor and mental images [47]. Motor Imagery (MI) is the cognitive modelling of bodily motions [48]. In contrast, motor and mental imagery are similar. However, rather than envisioning movements, an individual conducts alternative cognitive operations such as mental subtraction, auditory imagery, and spatial navigation [49].

This systematic review of the literature on implementing EEG on assistive devices in medical engineering seeks to be an exhaustive overview of present understanding regarding the use of technology to enhance EEG in controlling assistive devices and to detect the gaps that can be the subject of future study. Based on the analysis findings, The most probable areas for upcoming studies enhancement can be identified.

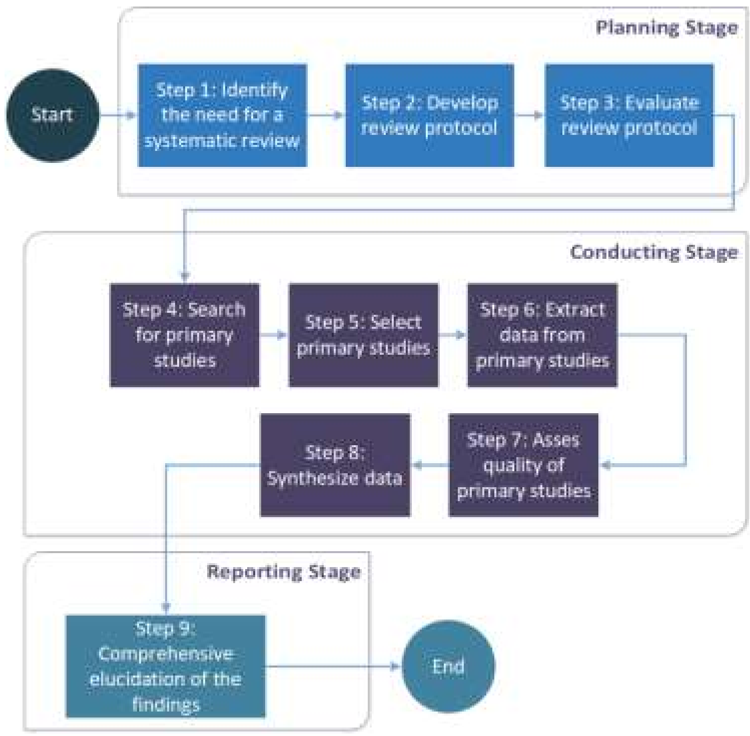

Figure 1. Systematic Literature Review Steps [3]

METHOD

Review Method

There are three steps to SLR, as shown in Figure 1: planning, conducting, and reporting the literature review. During the initial step, the requisites for a systematic review are set out (Step 1). As indicated in the introduction, a literature review seeks to find and evaluate relevant research on EEG application, particularly on controlling assistive equipment. The published systematic reviews on maintaining assistive devices using EEG studies are then assessed. The review approach was developed to provide instructions for the examination and diminish the potential of researcher bias (Step 2). The review protocol encompasses various aspects of the study, such as the approach employed for selecting relevant research, the inclusion/exclusion criterion, the research questions addressed, the strategy employed for searching, the evaluation of study quality, and the process of extracting and synthesizing data. These components are detailed in sections 2.2, 2.3, 2.4, and 2.5 of the protocol for evaluation. The review procedure was devised and subjected to testing.

Specific Research Questions (RQ) were developed to preserve the focus in the limited scope. They were devised per a set of rules of Population, Intervention, Comparison, Outcomes, and Context (PICOC)[1]. The research topics' PICOC structure is represented in Table 1.

Table 1. An Overview of PICOC

Population	Assistive Device, Biosignal.
Intervention	Machine Learning, Artificial Intelligence
Comparison	Without artificial intelligence.
Outcomes	EEG implementations in assistive devices, the most effective controlling methods.
Context	Research in the Field of Industry and Academia: Exploring the Use of Both Little and Huge Datasets.

This literature review is motivated by the study queries and motivations in Table 2.

Table 2. Research Questions on Literature Review

ID	Research Question	Motivation
RQ1	Which publication has the greatest impact on EEG in assistive devices?	Determine the most influential EEG journals in the field of assistive devices.
RQ2	Who are the most productive and influential EEG assistive device researchers by country?	Determine the most active and influential researchers by country who have significantly contributed to EEG research in assistive devices.
RQ3	What types of research topics are chosen by EEG researchers in assistive devices?	Determine EEG research topics and trends in assistive devices.
RQ4	Which type of EEG implementation in assistive devices is most prominent?	Determine EEG implementations typically used in assistive devices.
RQ5	What kind of methods are used for the EEG in assistive devices?	Determine opportunities and trends for the EEG method in assistive devices.
RQ6	What methodological enhancements are proposed for EEG-based assistive devices?	Determine the proposed methodological enhancements for EEG in assistive devices.

The primary study investigated techniques and data sets of the implementation of EEG in instruments to answer RQ4 through RQ6. Then, analyzing the forms and datasets (RQ4 to RQ6) determined which methods and datasets in the implementation of EEG to control assistive devices are significant and which are not. RQ4 to RQ6 are the most critical research queries, while RQ1 to RQ3 aid in comprehending the primary studies' context. RQ1 through RQ3 provide a brief overview and analysis of a particular area of EEG studies in assistive devices.

Search Strategy

First, search terms were derived from the PICOC framework, focusing on the Population and Intervention components. Next, additional search terms were extracted from the research questions. Then, relevant titles, abstracts, and keywords were examined to identify more search terms. Synonyms, alternate spellings, and antonyms of the words were also considered. Finally, boolean operators (ANDs and ORs) constructed a sophisticated search query and the specified standings. This study used the query search method from [50].

A search query with the keywords "controlling" and "wheelchair" was conducted within the specified parameters of "TITLE-ABS-KEY ("controlling" AND "wheelchair") AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017)) AND LIMIT-TO (SUBJAREA, "ENGI") AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "p") OR LIMIT-TO (SRCTYPE, "j"))". The search yielded a total of 261 metadata entries.

One hundred three metadata entries were found based upon keyword and document type "Conference Proceedings" and "Journal" in "TITLE-ABS-KEY ("EEG" AND "assistive device") AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017)) AND (LIMIT-TO (SUBJAREA, "MED") OR LIMIT-TO (SUBJAREA, "ENGI"))".

The last, a search was conducted using the keywords "Controlling, wheelchair and EEG" in "TITLE-ABS-KEY

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("controlling" AND "wheelchair" AND "EEG") AND (LIMIT-TO (PUBYEAR, 2022) OR LIMIT-TO (PUBYEAR, 2021) OR LIMIT-TO (PUBYEAR, 2020) OR LIMIT-TO (PUBYEAR, 2019) OR LIMIT-TO (PUBYEAR, 2018) OR LIMIT-TO (PUBYEAR, 2017)) AND (LIMIT-TO (SUBJAREA, "COMP") OR LIMIT-TO (SUBJAREA, "ENGI")) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (SRCTYPE, "p") OR LIMIT-TO (SRCTYPE, "j"))". The search resulted in a cumulative count of 50 metadata entries.

The 148 entries by refining search queries for each database were curated, focusing regarding titles, abstracts, and keyword. Simply English academic journals and proceedings of conferences were included, covering the period from 2017 to 2022, for a thorough investigation.

Study Selection

Inclusion and exclusion criteria guided the selection of primary research sources. Table 3 outlines these specifications.

Table 3. Criteria of Exclusion and Inclusion

Inclusion Criteria	Small to large-scale investigates in industry and academia datasets. Studies discussed and compared modelling performance in the field of EEG device implementation. The studies are in the conference and journal versions.
Exclusion Criteria	Studies that do not have a solid validation or do not include the experimental results of EEG implementation on assistive devices. Studies on EEG deployment on assistive devices and procedures in a non-EEG scenario. Studies not written in English.

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement on reporting consistency was followed for this comprehensive study., as seen in Figure 2.

The steps employed by PRISMA for conducting literature reviews are comprehensive and precise. This literature evaluates the use of EEG in assistive devices. The articles published in reputable international journals that are indexed will be analyzed. Article references are extracted from Scopus databases, which include journals and proceedings, such as IEEE Xplore, MDPI, Springer, Frontiers, and ScienceDirect.

The ultimate list of selected studies included 45 core research. The full texts of 45 investigations were then analyzed. Besides that, the criteria for exclusion and inclusion, the original studies' value, pertinent to the studies topics, then research similarities were taken into account—except for duplicate articles authored by the same individuals and appearing in multiple journals. Forty-five primary studies remained after excluding articles based on full-text selection. This report's concluding section provides an exhaustive listing of the studies selected for Appendix 1.

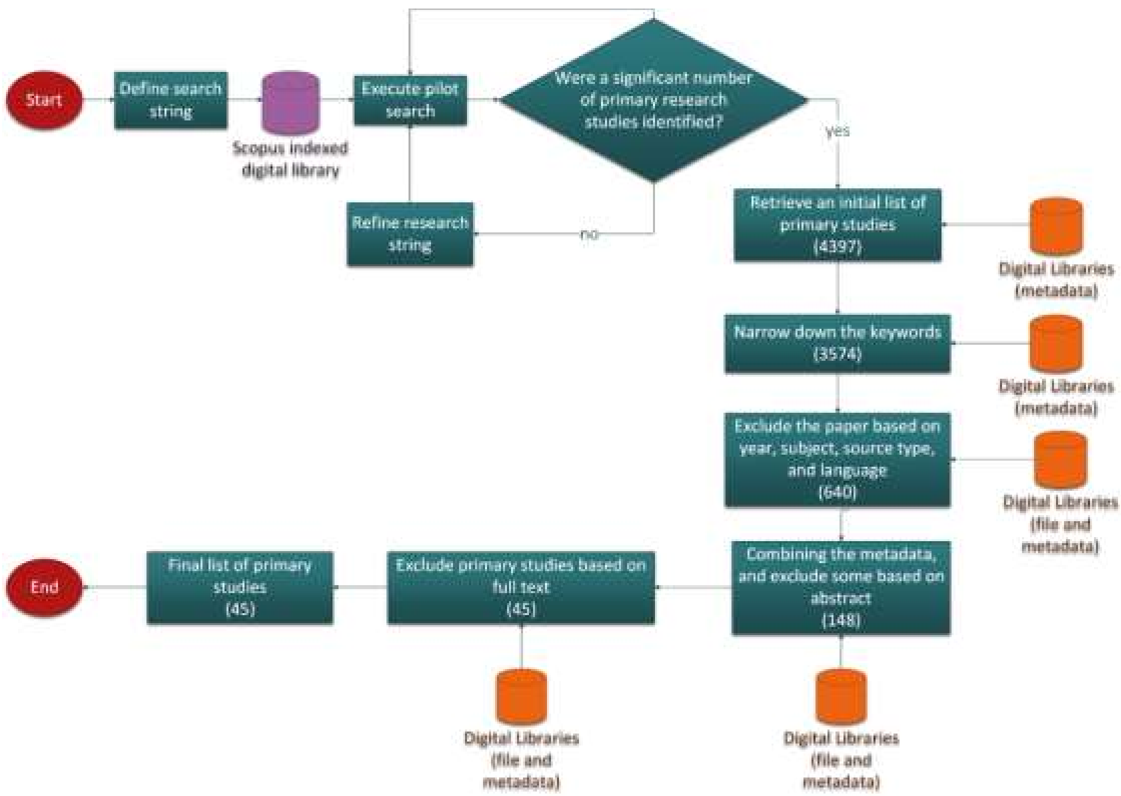

Figure 2. The Investigation and Identification of Primary Studies

Data Extraction

The results of iterative data extraction are depicted in Table 4.

Table 4. Data Extraction Properties Mapped to Research Questions

Property	Research Questions
Academic Studies and Publications	RQ1, RQ2
Research Topics and Tendencies	RQ3
EEG Implementation	RQ4
EEG Metrics	RQ4
EEG Methods	RQ5, RQ6

RESULTS AND DISCUSSION

Noteworthy Journal Publications

This research examined 45 main scholarly articles to investigate how EEG is used in assistive devices. Based on that, EEG implementation interest has increased since 2018. According to Figure 3, there will be 32 studies on EEG implementation by 2021, with four more expected to be added. From 2021 to 2022, nine articles were published, and more will likely be published in the following year.

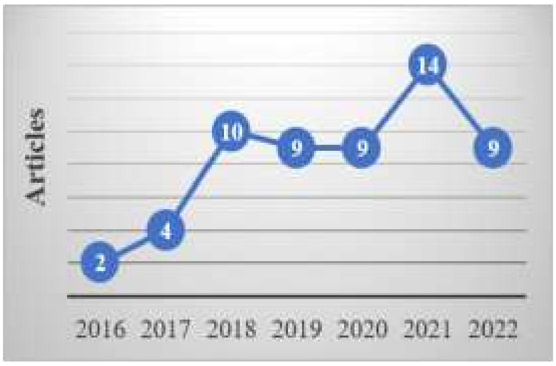

Figure 3. Analysis of the Distribution of Select Studies Over Time [51]

Figure 4 displays the most remarkable EEG implementation in assistive device journals, as the chosen vital research indicates. Both IFMBE and Frontiers in Neuroscience have the highest number of publications, with each journal having four articles. The journal/proceeding had the most articles published from 2016-2022.

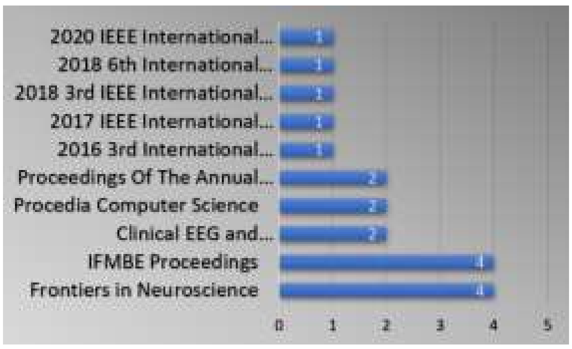

Figure 4. Publication in Journals and Distribution of Selected Studies [51]

The Country with the Most Proficient and Prominent Researchers

Table 6 shows a snapshot of the spread of studies done over the years by the country of the most active and influential researchers. Based on the three countries with the most articles about EEG application on assistive devices, the USA, India, and China, there are 30, 27, and 22 articles, respectively. So, it can be concluded that these three countries are aware of disability independence and are leaders in research on disability self-advocacy.

Table 6. List of Prominent Researchers by Country [51]

No	Country	Total
1	USA	30
2	India	27
3	China	22
4	Germany	21
5	Saudi Arabia	12
6	Pakistan	11
7	Australia	10
8	Denmark	9
9	Bangladesh	8
10	Switzerland	8
11	Turkey	8
12	Italy	7
13	Indonesia	6
14	Philippines	6
15	Spain	5
16	Mexico	4
17	Ecuador	3
18	Iraq	3
19	Jordan	3
20	UK	3
21	France	2
22	Israel	2
23	Japan	2
24	United Arab Emirates	2
25	Brazil	1
26	Canada	1
27	Norway	1
28	Romania	1
29	Singapore	1
30	South Korea	1

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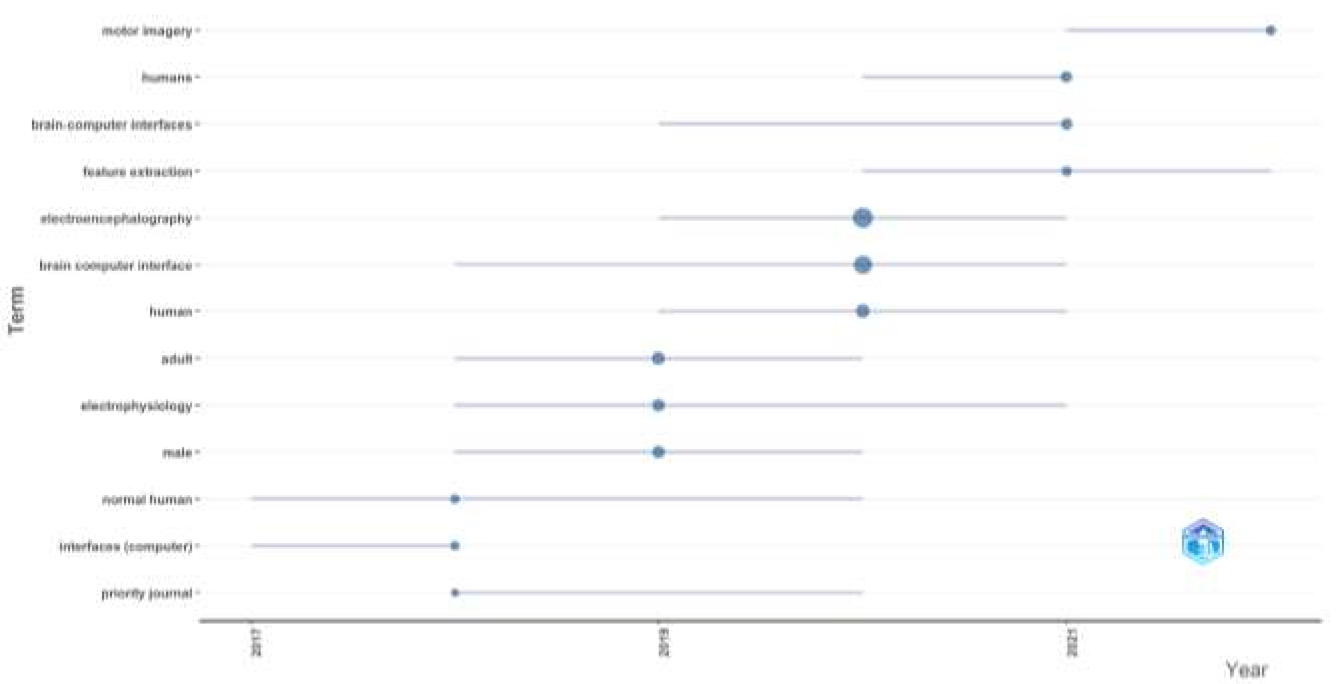

Figure 5. Trend Topics in "EEG on Assistive Device" from 2017 until 2022 [51]

Research Topics in EEG Implementation on Assistive Device

Figure 5 reveals the presence of many trend themes as identified by the keyword plus field in R Bibliometrix [51], [52]. The examination was conducted using specific criteria, incorporating a minimum word frequency threshold of three and a requirement for at least five words per year, including in 2019 with the issues of "adult," "electrophysiology," and "male". Then in 2020, topics were found regarding "electroencephalography", "brain computer interface", and "human". Then, in 2021, there were topics on the "human," brain-computer interfaces," and "feature extraction.".

From 2019 to 2021, 64 "electroencephalography"-related topics were discovered. There were 47 "brain computer interface" issues in 2018, 2019, 2020, and 2021. Each paper focuses primarily on EEG and BCI (assistive devices). These topics pertain to EEG applications. Appendix 1 also contains information about particular subjects.

EEG Implementation on Assistive Devices

The EEG technology has been vastly employed in operating assistive devices for individuals who suffer from disabilities. It comprises the rehabilitation of stroke patients [53], those with ALS [54], [55], and people with various disabilities [56], [57], [58], [59], [60]. Wheelchairs [61], [62] can be operated through the input of motor imagery [63], [64], facial muscle movements [65], blinks, and eye movements [66], [67]. Moreover, EEG can serve as a hearing aid [26], [43], [68], [69], [70] and control a robot arm through motor imagery [64], [71], [72] and SSVEP [73], [74] inputs. The top four applications of EEG are concisely outlined in Appendix 1

EEG Implementation Method

The 45 papers show diverse methods used to implement EEG to control assistive devices. Some studies classify EEG signal algorithms by using such as [53], [55], [58], [73], [74], [75], [76], Support Vector Machine [10], [59], [63], [65], [71], Convolutional Neural Network (CNN) [73], [74], [77], [78], [79], [80], CSP (Common Spatial Pattern) [63], [73], [76], [81], Threshold [66], [67], [82], [83], K-Nearest Neighbor [10], [84], [85], and Decision Tree [10], [83], [86]. The methods outlined are the six most frequently occurring; Appendix 1 provides additional information.

Some critical sources, such as Holtze et al. with cEEGrid for assisting hearing impairments, use EEGrid for system reliability [70]. Then, Jadhav et al. projected a new affordable wearable EEG device for assistive device control [68]. Because of its low cost, the system uses a microcontroller to detect eyeblink. Furthermore, Thong et al. made a brand-new EEG wireless portable recorder with their design [87]. They all propose their methods without needing a particular classification system.

Proposed Methods Improvements for EEG Controlling on assistive devices

Examining the primary sources and understanding the significance of disability-related independence led to realizing several appropriate things for the following research subjects. The first involves using input modalities that anyone may utilize without training, incredibly spontaneous EEG, face muscle activity, or motor/mental imagery. The best machine learning technique can then be compared to boost the system's reliability.

The facial muscle activity input control, for example, eyeblink, is an EEG artefact from EMG in the eye blink [12], [88], extensively used for controlling methods in prior studies [67], [80]. EEG artefacts are any signal that does not originate in the brain; this includes electrical, movement, and physiologic artefacts [89]. Therefore, research must emphasize whether to use aberrations that should be discarded or to eliminate artefacts from the EEG signal. In comparing motor/mental imagery and facial muscle activity, facial muscle activity is more practical and economical because the time required to familiarise the user with the assistive device is significantly shorter [90]. Regarding user universality, however, motor/mental imagery is preferable because some individuals with disabilities cannot move their facial musculature.

As for the system's dependability, it is preferable to employ multiple machine learning techniques and then compare them to determine the optimal accuracy, as demonstrated by Behncke et al. and Zhou et al., who compared deep CNN with a combination of rLDA and FB-CSP [73], and Deep Believe Network with SVM and Backpropagation Neural Network [63], respectively. Ramya et al. showed that it is possible to compare two or more methods in addition to juxtaposing them by using K-Nearest Neighbor for feature extraction and j48, Naive Bayes, and Random Forest classifiers to categorize the extracted results [84].

CONCLUSIONS

This systematic literature review examines EEG-based assistive devices in medical engineering from 2017 to 2022, focusing on trends and approaches. A total of 45 research were examined, with a focus on three key areas: electroencephalography, brain-computer interfaces, and human-machine interaction. The findings underscore the rising use of EEG in assistive technology such as wheelchairs, rehabilitation tools, hearing aids, and robotic limbs.

Linear Discriminant Analysis, Support Vector Machine, Convolutional Neural Network, and K-Nearest Neighbor are examples of classification algorithms that are often used and reflect various methods to improving accuracy. The review emphasizes the need of employing spontaneous EEG data, such as eye movements, for effective device control, as well as the need to distinguish genuine brain signals from artifacts. These findings help to accelerate the development and reliability of EEG-based assistive technology

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Appendix 1. The List of Primary Studies in the Field of EEG on Assistive Device

Year	Primary Studies	Publications	Publisher	Implementation	Methods	Trend Topics
2016	[43]	Frontiers in Neuroscience	Frontiers Media S.A.	In-ear EEG for hearing impairments	Multivariate Linear Regression	around-the-ear EEG for speech decoding
	[71]	Procedia Computer Science	Elsevier B.V.	Motor imagery-controlled Robotic arm.	Support Vector Machine and Genetic Algorithm	EEG 3 Degree of freedom controlled robotic arm
2017	[91]	Revista Mexicana de Ingenieria Biomedica	Sociedad Mexicana de Ingenieria Biomedica	Analysis of EEG in Locomotion	ANOVA	Feature extraction on EEG in locomotion
	[81]	Human Brain Mapping	John Wiley and Sons Inc.	Brain-Machine Interface	CSP Algorithm	EEG-fMRI
	[92]	2016 3rd International Conference on Electrical Engineering and Information and Communication Technology, iCEEiCT 2016	Institute of Electrical and Electronics Engineers Inc.	Wheelchair	N.A	ERS for BCI
	[87]	IFMBE Proceedings	Springer Verlag	Wireless EEG Recorder	Make a brand-new portable EEG recorder	Portable Wireless EEG Recording Device
2018	[93]	5th IEEE Region 10 Humanitarian Technology Conference 2017, R10-HTC 2017	Institute of Electrical and Electronics Engineers Inc.	Controller for home appliances by blinking signals	Threshold	Brain-drive, cognitive command
	[65]	Procedia Computer Science	Elsevier B.V.	Wheelchair controlled by facial muscle signal	Support Vector Machine and Wavelet Packet Transform	Facial Expression controlled wheelchair
	[54]	Clinical EEG and Neuroscience	SAGE Publications Inc.	Rehabilitation device on amyotrophic	Stepwise linear discriminate analysis (SWLDA)	Color stimuli for ALS individuals based on BCI
	[75]	2017 IEEE International Conference on Cybernetics and Intelligent Systems, CIS 2017 and IEEE Conference on Robotics, Automation, and Mechatronics, RAM 2017 - Proceedings	Institute of Electrical and Electronics Engineers Inc.	lateral sclerosis (ALS)	Multitier power spectral	Extracting Error-Related Potentials in
	[68]	2018 3rd IEEE International Conference on Recent Trends in Electronics, Information and Communication Technology, RTEICT 2018 - Proceedings	Institute of Electrical and Electronics Engineers Inc.	Detecting BCI error on Motor Imagery System	Density and A linear discriminant	Motion Imagery EEG
	[60]	Biocybernetics and Biomedical Engineering	PWN-Polish	Low-cost wearable EEG	analysis (LDA)	Brain modeling

Year	Primary Studies	Publications	Publisher	Implementation	Methods	Trend Topics
			Scientific Publishers	device for assistive device control		control systems
	[72]	International Journal of Intelligent Robotics and Applications	Springer	Communication pathway-based Tongue Machine Interface for severe disabilities.	Eye blink detection with microcontroller	GKP (Glossokinetic Potentials) to assist severe disabilities
	[73]	NEUROTECHNIX 2018 - Proceedings of the 6th International Congress on Neurotechnology, Electronics and Informatics	SciTePress	Motor imagery controlled 6-DOF robotic arm	Neural Networks	MI-Robot arm
	[74]	2018 6th International Conference on Brain-Computer Interface, BCI 2018	Institute of Electrical and Electronics Engineers Inc.	Robot design with SSVEP controlled	Multiple Regression	Robot error processing
	[26]	IFMBE Proceedings	Springer Verlag	Robot design with SSVEP controlled	Convolutional Neural Networks, Linear Discriminant Analysis (rLDA) and	Robot action error decoding
2019	[84]	Proceedings of IEEE International Conference on Signal Processing, Computing, and Control	Institute of Electrical and Electronics Engineers Inc.	Wearable EEG device	filter bank common spatial patterns (FB-CSP)	Low-cost EEG device
	[64]	Frontiers in Neuroscience	Frontiers Media S.A.	Motor Imagery EEG filtering	Convolutional Neural Networks, Linear Discriminant Analysis (rLDA)	BCI's best filtering method
	[66]	Proceedings of the 2019 2nd International Conference on Applied Engineering, ICAE 2019	Institute of Electrical and Electronics Engineers Inc.	MI-Wheelchair robot arm	Real-time FFT	Hybrid EEG-EOG for Wheelchair robot arm
	[59]	Neuroscience Letters	Elsevier Ireland Ltd	Wheelchair controlled by EEG-EOG	Random forest, Naive Bayes, KNN, and J48 classifiers	Hybrid BCI
	[62]	Proceedings - International Conference on Developments in eSystems Engineering, DeSE	Institute of Electrical and Electronics Engineers Inc.	Controlling fingers in the same hand	Supervised machine learning	Decoding BCI finger movements
	[94]	7th International Winter Conference on Brain-Computer Interface, BCI 2019	Institute of Electrical and	EEG wheelchair	Threshold	EEG-Wheelchair

 https://doi.org/10.25077/ajeeet.v4i2.42

Year	Primary Studies	Publications	Publisher	Implementation	Methods	Trend Topics
			Electronics Engineers Inc.			Control System Safety
	[63]	Proceedings - 2019 3rd International Conference on Data Science and Business Analytics, ICDSBA 2019	Institute of Electrical and Electronics Engineers Inc.	SSVEP Controlled Drone	SVM, Quadratic time-frequency distribution (QTFD) Choi–Williams distribution (CWD)	BCI Drone controlling
	[76]	IEEE Transactions on Industrial Informatics	IEEE Computer Society	Motor Imagery Wheelchair	N.A	EEG Intelligent wheelchair
	[95]	Electronics (Switzerland)	MDPI AG	Optimizing feature selection on MI	FFT	EEG MI Feature selection
2020	[77]	8th International Winter Conference on Brain-Computer Interface, BCI 2020	Institute of Electrical and Electronics Engineers Inc.	A review of HMI textile electrodes	Deep Belief Network	Daily wear HMI
	[85]	Computer Methods and Programs in Biomedicine	Elsevier Ireland Ltd	Decoding EEG signal on hand task	(DBN), OVO-CSP Algorithm, SVM	Deep learning EEG Decoding
	[82]	Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS	Institute of Electrical and Electronics Engineers Inc.	Any assistive device controlled with MI	LDA, CSP, RBFNN	Brain-Computer interface system
	[96]	International Journal of Social Robotics	Springer Science and Business Media B.V.	Estimating Reaction for Visual Stimulus	N.A	Motor imagery
	[69]	NeuroImage	Academic Press Inc.	Robotic Prostetic Control	CNN	SSVEP EEG Detects
	[67]	IFMBE Proceedings	Springer Verlag	Neuro-steered hearing aid	Flexible analytic wavelet transform (FAWT), k-NN	Automatic robotic prosthetic control
	[83]	Frontiers in Human Neuroscience	Frontiers Media S.A.	Eye Movement controlled wheelchair	SVC-RBF, Linear Regression, SGD, Decision Tree, Random Forest	brain-informed
	[78]	2020 IEEE International Conference on Multimedia and Expo Workshops, ICMEW 2020	Institute of Electrical and Electronics Engineers Inc.	Bilateral exoskeleton control	Weightless	speech

Year	Primary Studies	Publications	Publisher	Implementation	Methods	Trend Topics
	[79]	Frontiers in Neuroscience	Frontiers Media S.A.	MI Signal Decoding	Neural Network	separation
2021	[53]	2021 International Conference on Artificial Intelligence, ICAI 2021	Institute of Electrical and Electronics Engineers Inc.	MI-Drone controlled	2D convolutions long-short-term memory (LSTM) network	(BISS)
	[58]	IEEE Transactions on Neural Systems and Rehabilitation Engineering	Institute of Electrical and Electronics Engineers Inc.	MI-therapies for stroke patients	Threshold	Brainwave EEG Wheelchair
	[80]	Proceedings - 2021 15th International Conference on Advanced Computing and Applications, ACOMP 2021	Institute of Electrical and Electronics Engineers Inc.	Rehabilitation devices for motor impaired	MR-ERD detection threshold	BMI exoskeleton controlled by eyes
	[55]	Clinical EEG and Neuroscience	SAGE Publications Inc.	Assistive device control input	CNN	Deep learning EEG Decoding
	[57]	Computers and Electrical Engineering	Elsevier Ltd	Spellers for disabilities and ALS patients	4 class CNN	spatial-temporal self-attention
	[56]	Biomedical Signal Processing and Control	Elsevier Ltd	Rehabilitation tool for paralyzed people	Linear SVM, LDA, KNN, Logistic Regression, Kernel SVM	MI Classification
2022	[10]	Brain Sciences	MDPI	Translator disabilities intention	Simple Linear Discriminant Analysis	EEG natural hand decoding
	[70]	Frontiers in Neuroscience	Frontiers Media S.A.	MI pattern classification	CNN	EEG Classifier
	[97]	Neuroscience	Elsevier Ltd	cEEGrid for assisting hearing impairments	Stepwise linear discriminant analysis (SWLDA)	P300-based assistive device
	[98]	Sensors	MDPI	Remote Agent manipulation	Deep Learning	Intelligent EEG rehabilitation system

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