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Review

EEG in Neurorehabilitation can have Several Uses other than BCI: Biomarkers to Predict/Monitor Recovery

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Abbreviations

ALS, amyotrophic lateral sclerosis;
BCI, brain-computer interface;
DWT, discrete wavelet transform;
ECoG, electrocorticography;
EMD, empirical mode decomposition;
EEG, electroencephalography;
fMRI, functional magnetic resonance imaging;
IRB, institutional review board;
LiS, locked-in syndrome;
MCP, multiple country production;
NIRS, near-infrared spectroscopy;
SCI, spinal cord injury;
SCP, single country production;
SCPs, slow cortical potentials;
sTBI, severe traumatic brain injury;
WPD, wavelet packet decomposition

Abstract: Background: There is an increasing interest in the role of EEG in neurorehabilitation. We primarily aimed to identify the knowledge base through highly influential studies. Our secondary aims were to imprint the relevant thematic hotspots, research trends, and social networks within the scientific community. **Methods:** We performed an electronic search in Scopus looking for studies reporting on rehabilitation in patients with neurological disabilities. The most influential papers outlined the knowledge base, while a word co-occurrence analysis imprinted the research hotspots. Likewise, co-citation analyses highlighted collaboration networks between Universities, authors, and countries. The results were presented in summary tables, burst detection plots, and geospatial maps. Finally, a content review based on the top-20 most cited articles completed our study. **Results:** Our current bibliometric study was based on 874 records from 420 sources. There was a vivid research interest in EEG use for neurorehabilitation, with an annual growth rate as high as 14.3%. The most influential paper was the study titled "Brain-computer interfaces, a review" by Nicolas-Alfonso

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LF and Gomez-Gill J, with 997 citations, followed by "Brain-computer interfaces in neurological rehabilitation" by Daly J. and Wolpaw JR (708 citations). The USA, Italy, and Germany were among the most productive countries. The research hotspots shifted with time from the use of “functional magnetic imaging” to EEG-based “brain-machine interface”, “motor imagery”, and “deep learning”. **Conclusions:** EEG constitutes the most significant input in brain-computer interfaces (BCI) and can be successfully used in the neurorehabilitation of patients with stroke, amyotrophic lateral sclerosis, and traumatic brain and spinal injury. EEG-based BCI facilitates training, communication, and control of wheelchair and exoskeletons. However, research is limited to specific scientific groups from developed countries. Evidence is expected to change with the broader availability of BCI and improvement in EEG filtering algorithms.

Keywords: EEG; stroke; traumatic brain injury; neurorehabilitation; brain-machine interface

Introduction

After severe traumatic brain (sTBI) and spinal cord injury (SCI), stroke, and other neurodegenerative disorders, patients frequently suffer from significant neurological disabilities. Traditional rehabilitation focuses on teaching compensatory skills and allows the patient to return home as soon as possible but does not seem to reduce impairment [1,2]. Alternatively, functional recovery might result in more sustainable outcomes, as it has been associated with a long-term reduction in impairment and offers an improvement in the quality of life [1,2]. Thus, neurorehabilitation has recently shifted towards more active paradigms, particularly in patients with motor and communication handicaps [1,2]. Several approaches can improve motor learning, including massed and task-specific practice, multisensory stimulation, and motor imagery [1,2]. Similarly, intensive speech and language therapies, including constraint-induced aphasia therapy, which activates both the linguistic and concordant motor circuits, can rapidly improve language performance [1,2].

Lately, brain-computer interfaces (BCI), a communication system that recognizes a user's command only from the brain signals and reacts according to them, has been used in inpatient rehabilitation, with promising results [3,4]. Various invasive and non-invasive modalities, such as electroencephalography (EEG), near-infrared spectroscopy (NIRS), and electrocorticography (ECoG) [3,4], are frequently used to identify proper brain signals. High-density EEG constitutes an advanced and quantitative technique based on the multichannel recording of the brain’s electrical activity to localize the underlying brain structures [5]. To the best of our knowledge, there is paucity in the pertinent literature on quantitative studies reviewing the role of EEG in neurologic rehabilitation.

In our current study, we used bibliometrics, a systematic and reproducible way to review the literature based on the statistical analysis of highly cited records, to analyze and evaluate the literature regarding EEG in neurorehabilitation [6,7]. Bibliometrics are based on the assumption that the number of citations could reflect the impact or value of a particular article to a certain extent. We primarily aimed to identify the knowledge base through highly influential studies. Our secondary aims were to examine the relevant research front, focusing on active authors, thematic hotspots, and research trends. We also aimed to track the pertinent social networks within the scientific community regarding co-operations between institutions, Countries, and authors. By referring to this article, readers can apprehend literature trends and characteristics of scientific documents to gain insights to guide future studies.

Material and Methods

We conducted a bibliometric analysis according to the workflow recommended for science mapping (M. Aria and C. Cuccurullo), using the statistical environment R, the

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biblioshiny interphase (package bibliometrix) and VOSviewer [6,7]. Bibliometrix is a popular tool used for bibliometric analysis, particularly in health sciences [6]. Since we gathered literature data without involving any patients, the current study was exempted from Institutional Review Board (IRB) approval or patient informed consent [8].

Search strategy

Our electronic search was carried out in the medical database Scopus. We preferred the particular database as it is a broad database with many records and permits the extraction of scientometric meta-data [9,10]. To avoid duplicates and due to inherent software limitations, we limited our search to a single database. In this study, rehabilitation was defined as the field of science involved in neurologic recovery after sTBI, SCI, stroke and other central nervous system disorders such as amyotrophic lateral sclerosis (ALS) and locked-in syndrome (LiS) [11]. Neurologic rehabilitation included neural repair, regeneration, and dynamic reorganization of functional neural systems, manifested by increased awareness, and return to function and freedom [11].

Eligibility

We aimed to search titles, abstracts, and keywords for "rehabilitation", "neurological disorders", and "electroencephalography" in any form and combination (Table1). The search was limited to studies written in English in any form and without further limitations on the publication date. We intended to gather studies with significant impact, and therefore we decided to include any publication type, such as reviews, editorials, letters to the editor, and conference abstracts[12]. Our limitation in the manuscript language is not expected to change our results since English written articles have the largest penetration in health sciences[13]. We included all records resulting from the electronic search.

Table 1. Main bibliometric characteristics of documents retrieved from Scopus.

Description	**Results**
MAIN INFORMATION ABOUT DATA	
Timespan	1964:2021
Sources (Journals, Books, etc)	420
Documents	874
Average years from publication	5.03
Average citations per documents	21.63
Average citations per year per doc	3.13
References	41104
DOCUMENT TYPES	
article	546
book	1
book chapter	17
conference paper	145
conference review	4
editorial	18
erratum	1
letter	11

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note	5
retracted	1
review	119
short survey	6
DOCUMENT CONTENTS	
Keywords Plus	6146
Author's Keywords	1946
AUTHORS	
Authors	3589
Author Appearances	4623
Authors of single-authored documents	40
Authors of multi-authored documents	3549
AUTHORS COLLABORATION	
Single-authored documents	45
Documents per Author	0.244
Authors per Document	4.11
Co-Authors per Documents	5.29
Collaboration Index	4.28

Search in Scopus: (((TITLE-ABS-KEY (neurorehabilitation) OR TITLE-ABS KEY (rehabilitation AND neurological AND disorders OR TITLE-ABS-KEY (neuro-rehabilitation)))) AND (((TITLE-ABS-KEY (EEG) OR TITLE-ABS KEY (electroencephalography) OR TITLE-ABS KEY (electroencephalogram)))) AND (LIMIT TO (LANGUAGE, "English")).

Data collection

All citation data, bibliographical information, abstracts, and keywords of the eligible records were downloaded using the BibTeX format. We retrieved the article title, names and number of authors, year and journal of publication, Scopus citation count, and the corresponding author's country for our bibliometric analysis. Data was loaded on *biblioshiny* and analyzed without any further filtering [6].

Data analysis

The current study's data analysis occurred in two steps, using descriptive analysis and a network extraction process. We performed a descriptive analysis using standard competition ranking to retrieve evidence on the most productive authors and countries, the most cited papers, the most frequent journals, and the most common author's keywords [6]. In the network extraction process, we performed three sub-analyses, including a collaboration analysis according to Universities and countries, a co-citation analysis based on authors, and a word co-occurrence analysis according to the author's keywords [6]. To assess the extent of international collaborations, we used the indices of single country publications (SCP), multiple country publications (MCP), and the ratio of SCP over MCP [6,14]. In SCP, all authors belonged to the same country, representing intra-country collaboration [14]. On the contrary, authors belonged to different countries in MCP, and such publications represented an international collaboration [6,14].

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Data synthesis and Quality assessment

The results were presented in tables. Trends and temporal data were visualized in burst detection and simple time series plots. Word proximity maps were used to present the word co-occurrence analysis, the University collaboration analysis, and the author co-citation analysis. Geospatial data and conceptual structures were shown in geographic maps and cluster strings. Finally, after gathering and reading the full text of the top-20 most cited studies, we performed a narrative literature review.

Results

Literature search

The electronic search in Scopus resulted in 874 records from 420 sources (Table 1). Among the gathered documents, there were 456 original studies, 145 conference papers, and 119 reviews. With a total of 41,104 references, there was an average of 21.63 citations per document, while the average years after publication were as high as five. The numbers of Scopus and authors' keywords were 6,146 and 1,946, respectively. We recorded 3,589 authors, with 0.24 documents per author and 5.29 co-authors per document. There was a rising interest in EEG use in neurorehabilitation, with an annual growth rate as high as 14.3% during the last ten years (Figure 1, top).

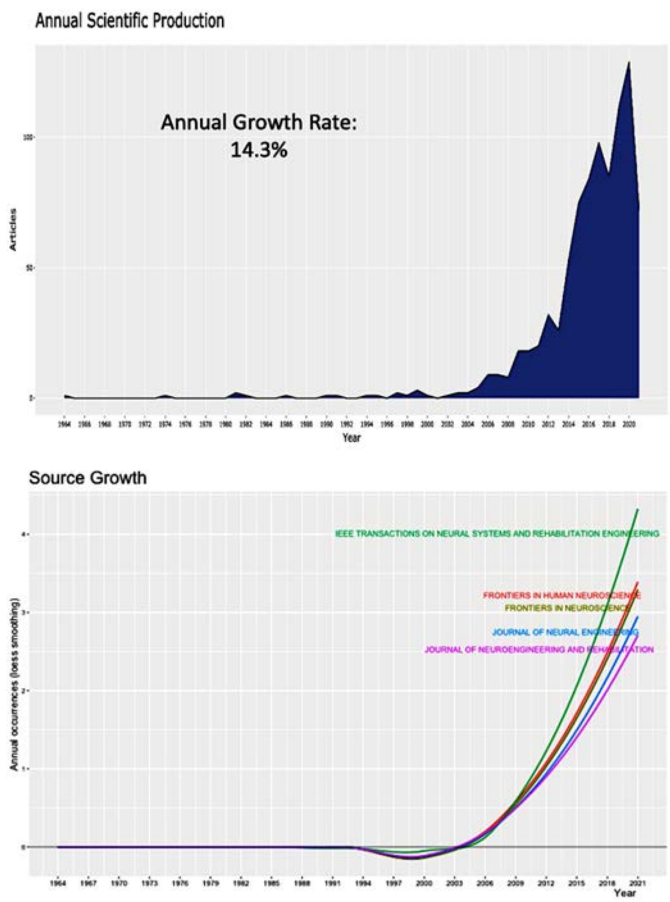

Figure 1. According to the annual scientific production (top) and source growth (bottom), there is a rising scientific interest in using EEG in neurorehabilitation.

Top-20 most cited documents

The list of the top-20 most cited articles is depicted in Table 2 [3,4,15–32]. The most cited document was “Brain-computer interfaces, a review” by Nicolas-Alfonso et al., (997 citations), followed by “Brain-computer interfaces in neurological rehabilitation” by Daly

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J and Wolpaw JR (708 citations) [3,4]. In this list, thirteen (65%) documents were reviews, six (30%) were research articles, and the remaining one (5%) was a symposium summary. Five studies (25%) involved stroke, whereas one article (5%) was related to sTBI, SCI, and ALS/LiS. Brain-computer interface (BCI) was the main topic in eleven (55%) studies. Finally, neurorehabilitation was used to improve motor function in 15 (75%) studies, whereas, in three (15%) and one (5%) studies, neurorehabilitation was implemented to control machines and facilitate communication.

Table 2. Top-20 most globally cited documents.

Paper	Year	Journal	Total Citations	Study design	Clinical entity	Main topic	Use
Nicolas-Alfonso L and Gomez-Gill J [3]	2012	*Sensors*	997	Review	Multiple	BCI	Rehabilitation
Daly J and Wolpaw J [4]	2008	*Lancet Neurol*	708	Review	Multiple	BCI	Rehabilitation
Ramos-Murguialday A et al. [15]	2013	*Ann Neurol*	521	Research	Multiple	BCI	Motion
Naseer N and Hong K [16]	2015	*Front Human Neurosci*	483	Review	Multiple	BCI	Motion
Young A and Ferris D [17]	2017	*IEEE Trans Neural Syst Rehabil Eng*	305	Review	Multiple	Exoskeleton	Motion
Chaudhary U et al. [18]	2016	*Nat Rev Neurol*	293	Review	Multiple	BCI	Communication
Kos D et al. [19]	2008	*Neurorehabil Neural Repair*	274	Review	MS	MS	Rehabilitation
Rizzolatti G et al. [20]	2009	*Nat Clin Pact Neurol*	268	Review	Multiple	Mirror neurons	Rehabilitation
Donati A et al. [21]	2016	*Sci Rep*	197	Research	SCI	BCI	Rehabilitation
Kevric J and Subasi A [22]	2017	*Biomed Signal Process*	194	Research	Multiple	BCI	Rehabilitation
Wagner J[23]	2012	*Neuroimage*	173	Research	Multiple	Robotics	Rehabilitation
Dobkin B [24]	2007	*J Physiol*	165	Conference	ALS, LiS	BCI	Rehabilitation
Lebedev M and Nicolelis M [25]	2017	*Physiol Rev*	162	Review	Multiple	BCI	Rehabilitation
Soekadar S et al. [26]	2015	*Neurobiol Dis*	156	Review	Stroke	BCI	Rehabilitation
Lew E et al. [27]	2012	*Front Neuroengineering*	153	Research	Stroke	EEG decomposition	Rehabilitation
Elbert T and Rockstroh B [28]	2004	*Neuroscientist*	152	Review	TBI	Plasticity	Rehabilitation
Obrig H [29]	2014	*Neuroimage*	151	Review	Multiple	NIRS	Clinical

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Ang K et al. [30]	2010	*Annu Int Conf IEEE Eng Med Biol Soc EMBC*	148	Review	Stroke	BCI	Rehabilitation
Altenmuller E et al. [31]	2009	*Ann New York Acad Sci*	146	Research	Stroke	Plasticity	Rehabilitation
Ramos-Murguialday A et al. [32]	2012	*PLOS One*	138	Research	Stroke	BCI	Rehabilitation

(BCI, brain-computer interface; MS, multiple sclerosis; EEG, electroencephalogram; NIRS, near-infrared spectroscopy; SCI, spinal cord injury; TBI, traumatic brain injury; LiS, locked-in syndrome).

Top-20 most productive authors

The top-20 most productive authors are depicted in Figure 2, while most cited countries, based on the first author's affiliation, are shown in Table 3. Pfurtscheller G, Birbaumer N, and Wolpaw JR occupy the top-three of the most cited authors with 975, 875, and 501 citations.

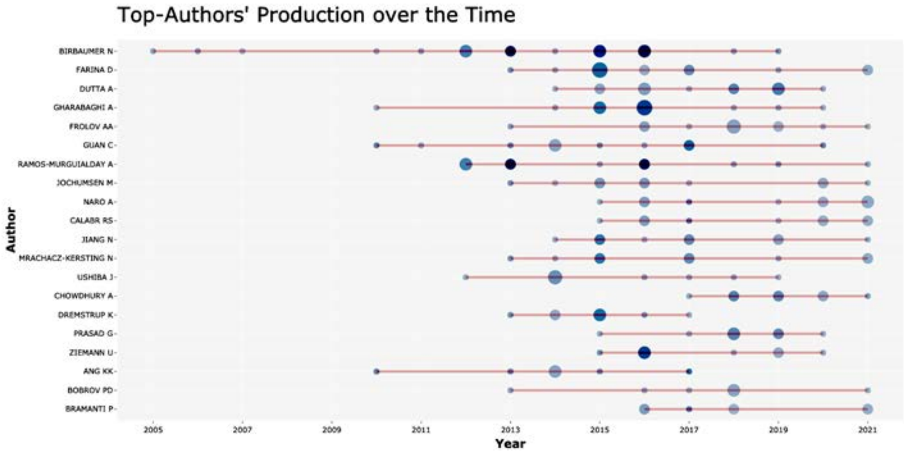

Figure 2. The figure shows the scientific production of the most influential authors.

Table 3. Top-20 scientific production by country.

Country	Articles	Frequency	SCP	MCP	MCP Ratio
USA	96	0,14	76	20	0,21
Italy	91	0,136	73	18	0,19
Germany	66	0,098	38	28	0,42
China	49	0,073	41	8	0,16
United Kingdom	40	0,059	24	16	0,4
Japan	34	0,050	32	2	0,06
Korea	33	0,049	28	5	0,15
Spain	28	0,041	11	17	0,60
Switzerland	22	0,033	14	8	0,36
India	20	0,03	15	5	0,25
Canada	17	0,025	9	8	0,47
Denmark	16	0,023	4	12	0,75
France	15	0,022	7	8	0,53
Austria	13	0,019	9	4	0,31
Poland	13	0,019	12	1	0,078
Australia	11	0,016	6	5	0,45

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Brazil	10	0,014	4	6	0,6
Belgium	9	0,013	5	4	0,44
Mexico	9	0,013	9	0	0
Singapore	8	0,011	3	5	0,62

SCP, single country publication; MCP, multiple country publication.

Top-20 journals

The gathered records were reported in 420 sources, and the top-20 journals were listed in Table 4. We witnessed an active source growth, particularly for the journals of "IEEE Transactions on neural systems and rehabilitation", "Frontiers in Human Neuroscience", "Frontiers in Neuroscience", and "Journal of Neural Engineering" (Figure 1, bottom).

Table 4. Top-20 most cited authors, sources, and keywords

Rank	Authors		Sources		Keywords	
	Name	Citations	Name	Articles	Words	Occurrences
1	Pfurtscheller G	975	*IEEE Transactions On Neural Systems And Rehabilitation Engineering*	27	neurorehabilitation	147
2	Birbaumer N	875	*Frontiers In Human Neuroscience*	23	eeg	115
3	Wolpaw J R	501	*Frontiers In Neuroscience*	22	stroke	105
4	Cohen L G	450	*Journal of Neural Engineering*	20	rehabilitation	78
5	Neuper C	438	*Journal of Neuroengineering And Rehabilitation*	19	brain-computer interface	74
6	Mcfarland D J	329	*Proceedings of The Annual International Conference Of The IEEE Engineering In Medicine And Biology Society EMBS*	18	motor imagery	64
7	Guan C	326	*Frontiers In Neurology*	16	electroencephalography	53
8	Farina D	286	*Neuroscience And Behavioral Physiology*	14	bci	37
9	Hallett M	284	*Neuroimage*	11	brain computer interface	30
10	Ang K K	276	*Neurorehabilitation And Neural Repair*	11	virtual reality	28
11	Blankertz B	275	*Clinical Neurophysiology*	10	disorders of consciousness	25
12	Gharabaghi A	266	*IFMBE Proceedings*	10	electroencephalography (eeg)	25
13	Scherer R	259	*Neurorehabilitation*	10	electroencephalogram	24
14	Makeig S	237	*Restorative Neurology And Neuroscience*	10	neurofeedback	23
15	Nitsche M A	219	*Lecture Notes in Computer Science (Including Subseries Lecture Notes In Artificial Intelligence And Lecture Notes In Bioinformatics)*	9	neuroplasticity	23
16	Ramos Murguialday A	218	*Sensors (Switzerland)*	8	transcranial magnetic stimulation	22
17	Paulus W	215	*Annals Of Physical And Rehabilitation Medicine*	7	brain-computer interface (bci)	21
18	Pascual Leone A	205	*Frontiers In Systems Neuroscience*	7	braincomputer interface	19
19	Schalk G	191	*Neural Plasticity*	7	brain-machine interface	18
20	Laureys S	189	*Biomedical Signal Processing And Control*	6	minimally conscious state	17

Top-20 most common author's keywords and word trends

The top-20 most common author's keywords and the trends regarding word growth are depicted in Table 4 and Figure 3. Except for the words "rehabilitation" and "electroencephalography" and their derivatives, the term "brain-computer interface" predominated among the author's keywords with 180 occurrences in various forms. We also recorded a rising trend in all keywords since 2005. However, the trends changed with time from the use of "function organisation magnetic imaging" to "brain-machine interface", "motor imagery", and "deep learning".

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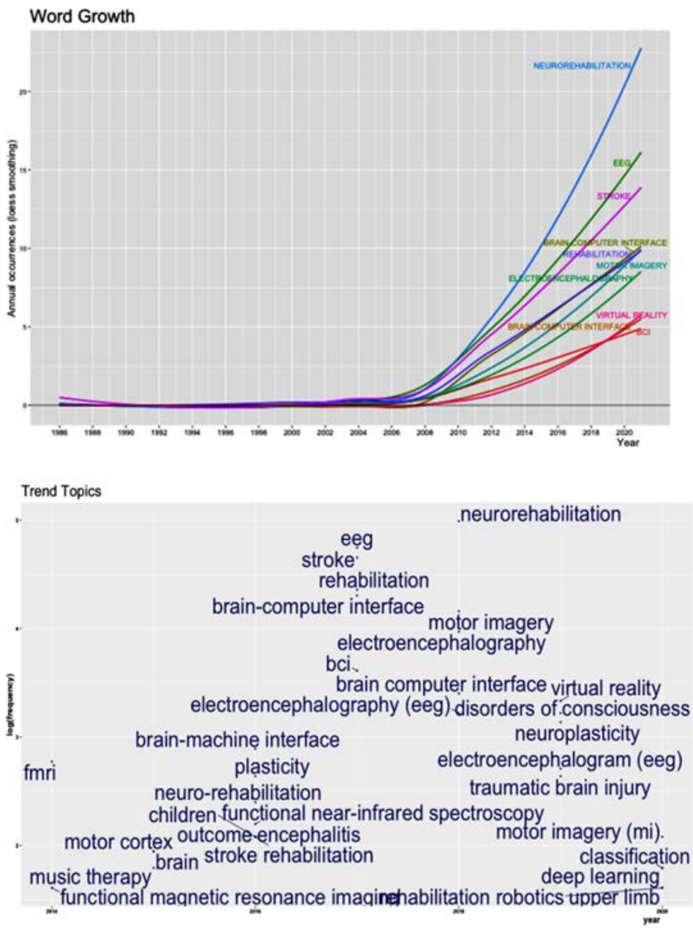

Figure 3. We noted important changes in the scientific trends with time, as recorded from the words growth (top) and trend topics (bottom) according to the author's keywords.

Collaboration analysis

According to the primary author, the USA, Italy, and Germany were the topmost productive countries. Based on the MCP/SCP ratio, many of the leading countries, such as the USA (21%), Italy (19.78%), and China (16%), were limited in local co-operations. In contrast, countries such as Denmark (75%), Singapore (62%), Spain (61%), France (53%), Canada (47%), Australia (45%), Belgium (44%), and Germany (42%) were involved in more extensive collaborations. Accordingly, the collaboration analysis map among institutions revealed a major co-operation network centred around the University of Lund (Figure 4, top). The remaining collaborations were limited to no more than a couple of institutions in every case.

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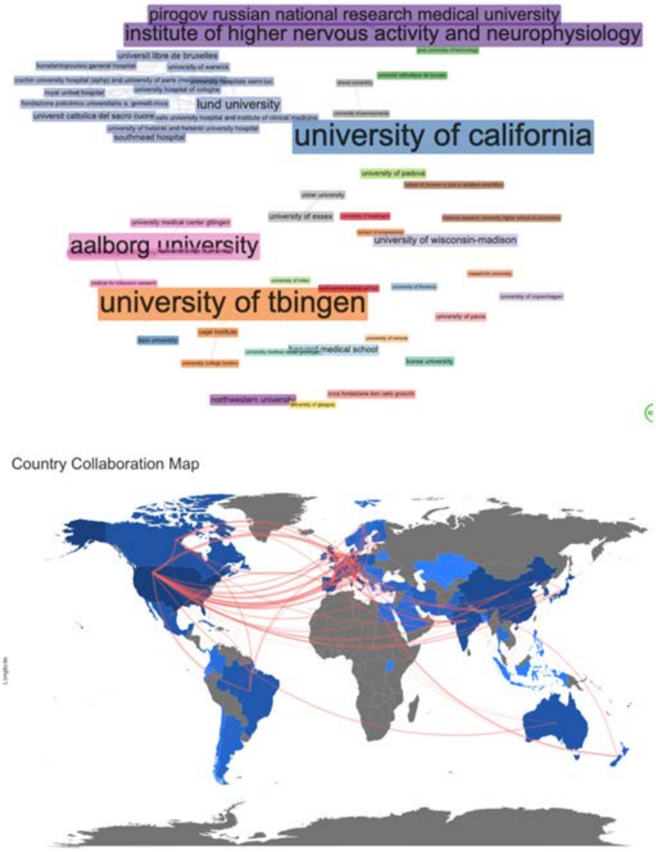

Figure 4. There are significant international collaborations among institutions and countries on the use of EEG in neurorehabilitation.

Co-word analyses

Basedsed on the author's keywords, the co-word analysis identified four major clusters (supplement Table 5). The keyword "motor imagery" characterized the first and fourth clusters. "Virtual reality" and the "disorders of consciousness" prevailed in the second and third clusters.

Table 5. Cluster analysis based on author's keyword co-occurrence.

Node	Cluster	Betweenness	Closeness	Page Rank
brain-computer interface (bci)	1	2,19	0,01	0,01
electroencephalography (eeg)	1	2,74	0,01	0,01
motor imagery (mi)	1	0,00	0,01	0,01
bci	2	2,98	0,01	0,03
eeg	2	215,55	0,01	0,08
fmri	2	0,42	0,01	0,01
p300	2	0,00	0,01	0,00
virtual reality	2	5,73	0,01	0,02
brain computer interface	2	0,84	0,01	0,02
emg	2	0,00	0,01	0,01
neuro-rehabilitation	2	0,00	0,01	0,01
cerebral palsy	2	0,13	0,01	0,01
disorders of consciousness	3	11,57	0,01	0,02
traumatic brain injury	3	3,13	0,01	0,01
minimally conscious state	3	4,93	0,01	0,02
vegetative state	3	7,70	0,01	0,02
outcome	3	0,63	0,01	0,01

prognosis	3	0,00	0,01	0,01
coma	3	0,38	0,01	0,01
unresponsive wakefulness syndrome	3	0,00	0,01	0,01
neurorehabilitation	4	513,51	0,02	0,13
brain-machine interface	4	0,49	0,01	0,01
brain-computer interface	4	42,45	0,01	0,04
electroencephalography	4	17,28	0,01	0,06
transcranial magnetic stimulation	4	1,38	0,01	0,01
electroencephalogram (eeg)	4	0,13	0,01	0,01
motor imagery	4	27,94	0,01	0,05
neurofeedback	4	2,39	0,01	0,02
event-related desynchronization	4	0,00	0,01	0,01
motor learning	4	0,16	0,01	0,01
functional near-infrared spectroscopy	4	0,02	0,01	0,01
electroencephalogram	4	0,89	0,01	0,01
spinal cord injury	4	0,24	0,01	0,01
brain-robot interface	4	0,00	0,01	0,01
functional connectivity	4	0,08	0,01	0,01
brain-computer interfaces	4	0,00	0,01	0,01
functional electrical stimulation	4	0,91	0,01	0,01
neuromodulation	4	0,00	0,01	0,01
stroke	5	132,77	0,01	0,09
rehabilitation	5	78,27	0,01	0,05
multiple sclerosis	5	0,00	0,01	0,00
neuroplasticity	5	1,04	0,01	0,01
plasticity	5	0,83	0,01	0,01
motor cortex	5	0,04	0,01	0,01
non-invasive brain stimulation	5	0,43	0,01	0,01
tdcs	5	0,64	0,01	0,01
transcranial direct current stimulation	5	1,60	0,01	0,01
motor control	5	0,00	0,01	0,00
exoskeleton	5	0,47	0,01	0,02
braincomputer interface	5	0,12	0,01	0,01

The cluster analysis was based on centrality measures, including betweenness, closeness, and page rank. Betweenness refers to the number of the shortest paths passing through a given node. The higher the betweenness centrality of the node, the greater the ability to control information passing between the other nodes. The closeness is used to measure the distance of one node to other nodes in a network. Nodes with high closeness centrality obtain information better than other nodes or tend to have a more direct influence on other nodes.

Review based on the top-20 most cited articles

The term brain-computer interface (BCI) refers to a hardware and software system that has been designed to control external computers or devices using cerebral signals [3,4,18,25]. In neurorehabilitation, BCI was used to assist severely disabled patients with sTBI, SCI, stroke, and ALS/LiS to interact with the environment [3,4,18,25,26] and work in five stages: (1) signal acquisition, (2) preprocessing or signal enhancement, (3) feature extraction, (4) classification, and the (5) control interface [3].

In signal acquisition, several brain signals, either electrophysiological or hemodynamic, are gathered invasively or non-invasively detected before further amplification, filtering, and decoding using online classification algorithms [3,4,18]. The slow cortical potentials (SCP), sensorimotor rhythms, P300 event-related potentials, steady-state visual evoked potentials, and cerebral oxygenation levels are frequently registered for this purpose [3,4,18]. Non-invasive modalities such as EEG, functional magnetic resonance

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(fMRI), and NIRS were the most extensively studied tools in recording brain activity since their invasive counterparts (ECoG and intracortical neuron recording) have been associated with significant health risks, including microelectrode rejection, infection, and tissue damage [3,16,18,29]. The primary motor and the prefrontal cortices were the preferred brain targets for EEC-based BCI and could be used in conjunction with NIRS in a hybrid technology [16,29]. In an experimental study, Lew et al. focused on the non-invasively recorded readiness potential, a SCP detected over the central medial areas [27]. The authors documented a high SCPs detection rate 500ms before movement onset. The absence of SCPs during the non-movement intention period allowed the authors to conclude that it could be a valuable tool in neurorehabilitation[27].

Signal preprocessing or enhancement involves signal amplification and noise removal [3,4,25]. EEG signals generated by motor task imagery could be translated into external actions [22]. However, the processing of EEG signals, which directly affects classification accuracy, still represents a crucial challenge. They are susceptible to several factors, including the physical state, mood, posture, and external noise [22]. Kevric et al. compared three EEG signal processing techniques, the empirical mode decomposition, discrete wavelet transform, and wavelet packet decomposition, to decompose EEG signals in a BCI system and task classification [22]. The authors reported that the highest classification (92.8%) was achieved by combining multiscale principal component analysis de-noising and higher-order statistics features extracted from wavelet packet decomposition subbands. The latter could be used to control external devices, including a wheelchair [22].

On the other hand, brain activity signals come in specific patterns, which need to be recognized, selected, extracted, and matched to the patient's intention, using classification or regression algorithms [3,4,25]. Regression algorithms employ EEG features as independent variables to predict user intentions [3]. In contrast, classification algorithms use the features extracted as independent variables to define boundaries between the different targets in feature space [3].

The ultimate goal is to use EEG-based BCI and help paralyzed disabled patients to communicate and control their environment, including external robotic devices and prosthetics, as in patients with ALS/LiS [3,4,17,18,26]. In addition, the recovery of neural function and motor function restoration in patients after stroke or SCI could be facilitated based on rehabilitative BCIs in conjunction with virtual reality-assisted training and behavioural physiotherapy by inducing neural plasticity [3,4,18,20,23,26,28]. Indeed, the addition of BCI training to behaviorally oriented physiotherapy could induce functional improvements in motor function in chronic stroke patients without residual finger movements and may open a new door in stroke neurorehabilitation [15]. Motor imagery represents a challenging method in rehabilitating stroke patients by promoting the recruitment of the motor system for functional recovery [30]. It involves attempts to execute imagined movements using the plegic hand [30]. Ang et al. tried to investigate 54 hemiparetic stroke patients' ability to operate an EEG-based motor imagery BCI [30]. In addition, they compared EEG-based MI-BCI in conjunction with robotic feedback neurorehabilitation to robotic rehabilitation that delivers movement therapy in terms of motor improvement on the stroke-affected upper limb [30]. The authors reported significant gains in the functional scores in post-rehabilitation and the two-month follow-up [30]. Of note, there were no significant differences between groups [30]. Motor outcomes could be potentiated using proprioceptive BCI in patients with residual proprioception and sessions of music-supported therapy [31,32]. However, there were cases where neuroplastic alterations were driven into maladaptive domains with significant adverse symptoms, such as phantom limb pain [28].

Equally important, EEG controlled exoskeletons were designed as assistive devices for individuals with disabilities but could also be used in rehabilitation to assist or resist passive and active movement [17,26]. Assistive technologies provided support and balance during walking and whole-body navigation using a wheelchair [17,25,26]. Therapeutic devices target the improvement of physiological health by increasing physical activity

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and weight-bearing capabilities [17,26]. Based on evidence that active contribution to the movement could be critical for encoding motor memory, Wagner et al. proposed brain monitoring techniques during gait training to encourage active participation [23]. Thus, the authors compared the spectral patterns in the EEG during active walking and passive robot-assisted walking [23]. Independent EEG components were clustered across participants based on their anatomical position and frequency spectra [23]. The authors provided evidence for significant cortical activation differences between active and passive robot-assisted gait [23]. They noted significant suppression of the mu, beta, and gamma rhythms during active walking, particularly compared to passive walking [23]. These differences depended on the phase of the gait cycle [23]. Similar differences were recorded in the right-hand area [23].

It seems that the use of EEG and BCI in neurorehabilitation was associated with significant limitations. Initially, there was a substantial lack in the literature of large randomized controlled clinical trials using invasive and non-invasive BCIs with long-term follow-up in patients rather than healthy populations [3,18]. In addition, BCI systems must become safer, more reliable, cosmetically acceptable, user friendly, and highly accurate [24]. The high cost of BCI technologies may raise ethical concerns, particularly in patients with ALS/LiS on ventilatory support [24].

Discussion

Overview of our findings

Our current manuscript presents a detailed analysis of the top-cited articles on the use of EEG in neurorehabilitation. It can help clinicians and researchers understand the existing knowledge base, comprehend the current research front, and get acquainted with the underlying social/scientific networks. We specifically identified the articles that served as landmarks in the field and the most influential authors. Likewise, we showed that the available research front originates from a limited number of Institutions with an even smaller number of co-operations among them. Finally, it became evident that most research originates from affluent countries from Europe and the USA, with little to minimal contribution from Asia and the Americas. BCI constitute the connecting link between EEG and rehabilitation. This study seems to be the first study focusing on a specific topic. Therefore, there are no relevant studies that can be used for further comparison. Nevertheless, a series of thoughts have been elicited by the current findings and are presented thereunder.

Bibliometrics

Bibliometrics is a viable means to review the literature qualitatively and quantitatively [6,7,14,33]. It is an analysis of “big data” originating from literature databases, using artificial intelligence (AI) [34]. It is based on the concept that highly cited articles have a significant impact on the development of science [35]. Accordingly, we could identify the research background of the most active authors, countries and institutions, and journals[36]. The research trends and hotspots could be identified based on the most frequent author’s keywords and their changes with time. Finally, various networks between authors, countries, and institutions could be recognized based on word co-occurrence analysis.

Temporal trends

Neurorehabilitation and control of external devices using EEG-based BCI were characterized by a recent rise of scientific interest and a high annual scientific production. Even though motor and communication disabilities occurred as long as humanity existed, this rise occurred in the last decade. Several scientific advances preceded, including the development of AI and several signal filtering algorithms [37,38]. Thus, we recorded an expo-

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nential rise in scientific production since the early 2010s. There are probably two additional reasons why EEG in neurorehabilitation showed this late bloom. There was a shift in the rehabilitation approach from teaching patients to cope with disability towards improving the functional outcome by neurorehabilitation [3,4,25]. Furthermore, the use of EEG in neurorehabilitation demands a deep understanding of brain function and thorough computer science knowledge [39]. It seems that these disciplines reached fruitful crossroads only recently.

Journal preferences

Analysis of the sources showed that publications on the use of EEG in neurorehabilitation are published in journals focusing on engineering and biomedical signals, rehabilitation, and neurosciences. These journals pioneer in hosting articles at the crossroads of neurosciences with other disciplines, particularly bioengineering. Indeed, the exponential rise in BCI research and the use of exoskeletons shifted authors and editors to journals merging neurosciences and engineering. It is worth noting that classical medicine and neurology journals are absent from the top-20 most cited journals.

Geographical distribution

The current study demonstrated two significant controversies. To start with, the majority of the studies come from affluent countries of the US and Europe. Asia and the Americas are represented to a lesser extent, with a minimal contribution from Africa. This map follows the rehabilitation requirements after stroke in affluent countries with older populations and less by craniospinal trauma in developing countries [40,41]. It remains to be shown if a similar distribution exists in lower-income subgroups within the affluent countries. The second controversy is that the leading countries prefer a more self-sufficient approach instead of participating in extensive international collaborations. Indeed, it seems that "elite players" such as the USA, Italy, and China prefer lonely paths. At the same time, smaller partners, like Denmark, Singapore, Spain, and others, are more interested in international collaborations.

Document type

In the present review, we focused on studies with the highest impact in the field. We decided to include all document types, in addition to original studies, as we noted that reviews and conference papers and reviews were among the highly ranked documents in our initial pilot searches. The presence of reviews in our study highlights the need to spare time and resources from exhaustive searches in a rapidly evolving field. In addition, the large number of conference papers among the highly cited documents shows that a significant part of the evidence has not been published in peer-reviewed journals, raising several questions on the reproducibility of the findings and the role of funding in research.

Limitations

Significant limitations characterized the current study. Firstly, it was based on bibliographic data from Scopus due to inherent limitations of the adopted software and to avoid duplicates, as explained earlier. However, we selected Scopus since it is the single largest extractable medical database with the most useful scientometric data. Secondly, a bibliometric analysis lacks an in-depth analysis of the gathered articles. For this reason, we added a content review of the 20 most cited articles. Thirdly, a higher citation index is not necessarily synonymous with better methodological quality and improved reporting clarity. In other words, a bibliometric analysis could include low-quality studies but with a significant impact in the field. Likewise, our study could omit high-quality studies that are still immature to reach a high citation number. Therefore, the reader is cautioned that our results are expected to change, and regular literature updates are mandatory in the future. Finally, a bibliometric analysis may result in a limited number of irrelevant articles

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after reading the document's full text. One (5%) irrelevant study was found among the top-20 results in our sample [19].

Conclusions

EEG constitutes the most significant input in brain-computer interfaces (BCI) and can be successfully used in the neurorehabilitation of patients with stroke, ALS/Lis, sTBI, and SCI. EEG-based BCI facilitates training, communication, and control of wheelchair and exoskeletons. However, research is limited to specific scientific groups from developed countries. In addition, there seems to be unpublished evidence with significant impact. Evidence is expected to change with the broader availability of BCI and improvement in EEG filtering algorithms.

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