Review

Not peer-reviewed version

The Bibliometric Analysis of EEGLAB software in the Web of Science indexed Articles

Mohammad Fayaz *

Posted Date: 16 October 2023

doi: 10.20944/preprints202310.0940.v1

Keywords: EEGLAB, Bibliometric Analysis, Computational Neurosciences, MATLAB, R,

Review

The Bibliometric Analysis of EEGLAB Software in the Web of Science Indexed Articles

Mohammad Fayaz

PhD in Biostatistics, Lecturer in Statistics, Allameh Tabataba'i University, Tehran, Iran; mohammad.fayaz.89@gmail.com

Abstract: Introduction: EEGLAB is one of the most famous software for processing, analyzing, and researching experiments that have Electroencephalography (EEG) datasets. Due to the numerous and famous add-ins along with global, widespread communications and online free training, its popularity increased every year. **Method**: To address this phenomenon from a bibliographic perspective, we found 20,464 citations in Google Scholar for the main EEGLAB reference since 8/27/2023. Then, only the Web of Science (WOS) articles were 12,700 that they were extracted. The results were analyzed with Bibliometrix package from CRAN R software. **Results**: The time span of these articles is from 2004 to 2023 with 12,700 documents in 1,125 sources (journals, books, etc.), 29,125 authors, 19,062 author's keywords, 13,707 keywords PLUS, 279,617 references. The annual growth rate is 28.12 %, international Co-authorship is 37.27 % and Co-authors per document is s 4.89 and the average citations per document is 22.51. The most relevant sources are Neuroimage, Frontiers in Human Neurosciences, Scientific Reports, Psychophysiology, and PLOS One with 780, 526, 446,425, and 371 articles, respectively. The most cited countries are the USA, Germany, and the United Kingdom with 93,093, 32,621, and 20,748 total citations, respectively. The ERPLAB, ADJUST, and ICLabel add-ins have the local to global citation ratios equal to 85.4%, 65.1%, and 78.2% respectively. Other bibliometric analyses such as co-occurrence networks and thematic maps of abstracts, titles, and keywords are estimated and presented. **Conclusions**: EEGLAB is among the most cited MATLAB toolboxes in computational neuroscience. Many developed and developing countries use it in their research publications.

Keywords: EEGLAB; bibliometric analysis; computational neurosciences; MATLAB; R

Highlights:

- Summarizes 12,700 ISI-indexed articles about EEGLAB.
- Clustered Collaboration Network University into 6 segments.
- Presented the trend topics plot for keyword plus.
- Presented Co-Citation Network of authors for all and core sources.
- Have a big Supplementary Materials for further analysis and reproducible results.

1. Introduction

The EEGLAB was presented as MATLAB (http://www.mathworks.com/) open-source toolbox in a research publication in 2004 by Arnaud Delorme and Scott Makeig from Swartz Center for Computational Neuroscience, Institute for Neural Computation, University of California San Diego, USA [1]. It has an interactive graphical User interface (GUI) with independent component analysis (ICA), Time/Frequency Analysis (TFA), and more than 150 plug-ins for example Fieldtrip-lite [2] , ERPLAB [3], ICLabel [4], SIFT [5] , AMICA [6], PACT [7] and LIMO [8] to analyze dynamic brain data. (https://sccn.ucsd.edu/eeglab/plugin_uploader/plugin_list_all.php)

Although it is not the only software in neuroscience research, it has a big community of users and developers from different countries and various expertise in neurosciences, biomechanics, Psychology, Bioengineering, Biosignal processing, Neuromechanics, Rehabilitation, Software engineering, Biostatistics, and data science. Also, it is used with other software for EEG- fMRI (Functional magnetic resonance imaging) datasets with SPM (Statistical Parametric Mapping) [9], EEG-NIRS (near-infrared spectroscopy) dataset with BBCI Toolbox [10], BCILAB in brain–computer

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 October 2023 doi:10.20944/preprints202310.0940.v1

interface (BCI) development [11], in R packages like neuroconductor [12] and medical researches [13] and the Virtual Brain (TVB) [14,15].

The systematic reviews and meta-analysis studies about EEG were highly cited and popular for example Default-mode brain dysfunction in mental disorders [16], deep learning [17], feature extraction [18] and meta-analysis for randomized controlled trials for Nonpharmacological interventions for ADHD [19]. But the bibliometric analysis is new and was limited to the application of EEG indices in human cognitive performance with 143 items [20], Mild Cognitive Impairment (MCI) research with 2310 items [21], mental fatigue on athletic performance with 658 items [22], Quantitative EEG in neuropsychiatric field with 1904 articles [23], neuromarketing with 30 items [24] and 24 items [25], Consumer Neurosciences with 364 items [26], consumer behavior and marketing with 497 items [27] , strategic management studies with 105 items [28] ,Neurorehabilitation with 874 items [29], Neuroarchitecture Assessment with 295 items [30] and Construction [31].

Sometimes bibliometric analysis is combined with different text mining methods such as topic modeling and word clouds. They show the most important words in a text by statistical and machine learning methods [32,33]. The recent study of AI-enhanced human EEG analysis with 2,053 research items presented world clouds [34]. In this study, we present the bibliometric analysis with some text mining methods for aggregated abstracts by using the bibliometrix R package for all available ISI research articles that have been cited the EEGLAB [35].

2. Materials and Methods

2.1. Data Gathering

The EEGLAB was introduced in the "Delorme A, Makeig S. EEGLAB: an open-source toolbox for analysis of single-trial EEG dynamics including independent component analysis. Journal of neuroscience methods. 2004 Mar 15;134(1):9-21." [1]. Since 8/27/2023, there have been 20,464 citations in the Google Scholar. It consists of different types of articles, proceedings, poster presentations, etc. In this research, only available items in the Web of Science (WOS) Core Collection (2001-present) have been collected from webofknowledge.com. It consists of four databases: 1) Science Citation Index Expanded (SCI-EXPANDED)--2001-present, 2) Social Sciences Citation Index (SSCI)--2001-present, 3) Arts & Humanities Citation Index (AHCI)--2001-present and 4) Emerging Sources Citation Index (ESCI)--2018-present. The available items were 12,700 (~62.1% of all Google Scholar citations) and they were collected, integrated, and saved with bib format file. They were not all references such as only SCOPUS indexed journals, but only articles published by the Institute for Scientific Information (ISI) journals.

2.2. Data Analysis

The data and bibliography analysis were conducted with Bibliometrix [35] package in R studio 2023.06.1 and R Core Team (2022). [36]

3. Results

3.1. Descriptive Statistics

The timespan is from 2004 to 2023 with 12,700 documents published in 1,125 ISI-indexed sources (journals, books etc.), written by 29,125 authors, including 19,062 author's keywords, 13,707 keywords PLUS and 279,617 references. The annual growth rate of publication is 28.12 %, international Co-authorship is 37.27 % and Co-authors per document is 4.89 and the average citations per document is 22.51. According to the Clarivate website, *the keyword PLUS are words or phrases that frequently appear in the titles of an article's references, but do not appear in the title of the article itself.*

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 October 2023 doi:10.20944/preprints202310.0940.v1

3.2. Sources

The most relevant sources are Neuroimage, Frontiers in Human Neurosciences, Scientific Reports, Psychophysiology and PLOS One with 780, 526, 446,425 and 371 articles. According to the Bradford's Law, these first five journals plus Journal of Neuroscience, Neuropsychologia, Clinical Neurophysiology, Frontiers in Neuroscience, Journal of Cognitive Neuroscience and International Journal of Psychophysiology have 4,318 (34.00%) articles and they are categorized as the core sources. These articles came from 11 out of 1,125 sources and they have 12,062 out of 29,125 authors. The local impact of the first five journals is presented at Table 1.

Table 1. The Local Impact by Journals and Indices.

Sources	Local Impact			Total Citations	Number Papers	Start Year
	H Index	G Index	M Index			
NEUROIMAGE	87	135	4.57	31,446	780	2005
JOURNAL OF NEUROSCIENCE	73	123	3.84	18,584	310	2005
FRONTIERS IN HUMAN NEUROSCIENCE	53	90	3.53	12,074	526	2009
PLOS ONE	50	79	2.94	9,755	371	2007
PSYCHOPHYSIOLOGY	48	94	2.52	11,230	425	2005

According to the definition of the Hirsch-index or H-index, "A scientist has index h if h of his or her N_p papers have at least h citations each and the other $(N_p - h)$ papers have fewer than $\leq h$ citations each." [37] The g-index is introduced as an improvement of the h-index to measure the global citation performance of a set of articles [38] It is the highest number g of papers that together received g^2 or more citations. The M-Index definition is " $\frac{h}{y}$ where $h = h - index$, $y = number\ of\ years\ since\ publishing\ the\ first\ paper$." [39]. According to Table 1 , Neuroimage journal has the highest values of H-Index, G-Index ,and M-Index and total citations.

3.3. Authors

Some results of author analysis are not very reliable, because many author names have the same abbreviations especially in Chinese first and last names and their unique ORCID code is not available. Therefore, only related analysis was reported that the names are famous and related to the specific person.

The 19,416 (66.7%), 4,432 (15.2%), 1,879 (6.5%) and 292 (1.0 %) authors have only 1, 2, 3 and 7 articles, respectively. The most cited countries are the USA, Germany and the United Kingdom with 93,093, 32,621 and 20,748 total citations, respectively. The collaboration network between universities is estimated and clustered with Walktrap method into 6 clusters. [40] According to Figure 2, the biggest cluster is yellow with the University of California San Diego (UC) where the Swartz Center for Computational Neuroscience located, the hosting lab of EEGLAB. The red, green and brown clusters have only German, Chinese and European countries universities, respectively. The clusters also have relationships between each other. The university name and their countries are listed in Table 2.

Preprints (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 October 2023 doi:10.20944/preprints202310.0940.v1

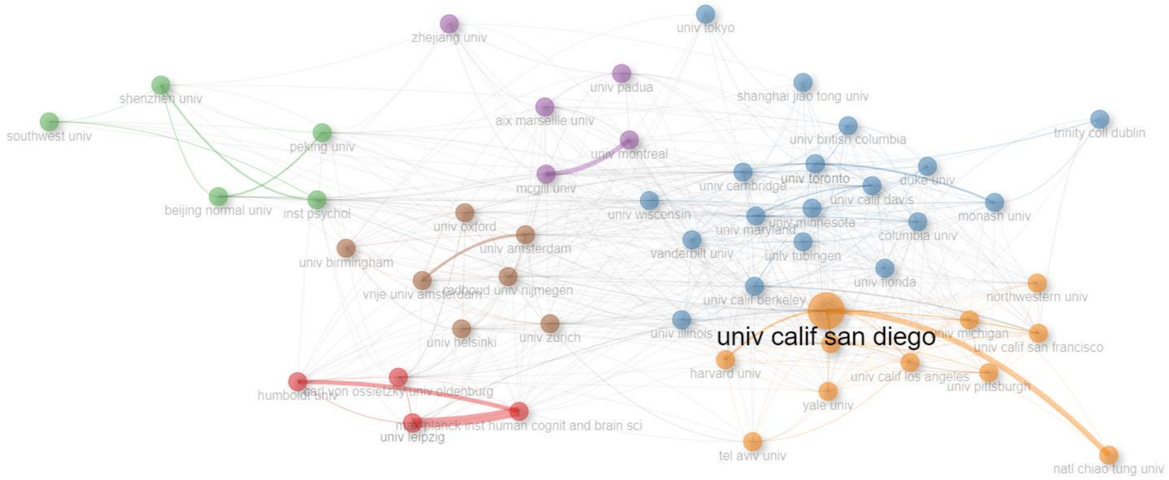

Figure 2. Collaboration Network University (6 Clusters).

Table 2. The Collaboration Network Universities.

Row	Cluster	Color	Universitas (Countries)*
1	1	Red	carl von ossietzky univ oldenburg (Germany), univ leipzig (Germany), humboldt univ (Germany), max planck inst human cognit and brain sci (Germany)
2	2	Blue	univ toronto (Canada), univ calif davis (USA), univ maryland (USA), univ cambridge (UK), univ wisconsin (USA), univ illinois (USA), univ tubingen (Germany), monash univ (Australia), univ minnesota (USA), univ british columbia (Canada), trinity coll dublin (Ireland), univ calif berkeley (USA), columbia univ (USA), univ florida (USA), shanghai jiao tong univ (China), vanderbilt univ (USA), univ tokyo (Japan), duke univ (USA)
3	3	Green	beijing normal univ (China), southwest univ (China), inst psychol (?), peking univ (China), shenzhen univ (China)
4	4	Purple	univ padua (Italy), mcgill univ (Canada), aix marseille univ (France), zhejiang univ (China), univ montreal (Canada)
5	5	Orange	univ calif san diego (USA), harvard med sch (USA), univ pittsburgh (USA), northwestern univ (USA), tel aviv univ (Israel), univ michigan (USA), univ calif los angeles (USA), univ calif san francisco (USA), natl chiao tung univ (Taiwan), yale univ (USA), harvard univ (USA)
6	6	Brown	univ zurich (Switzerland), univ helsinki (Finland), univ oxford (UK), radboud univ nijmegen (Netherlands), univ amsterdam(Netherlands), vrije univ amsterdam (Netherland), univ birmingham(UK)

*Abbreviation name of universities (Country name)

We also estimate the collaborations between countries. In this regard, we only consider 50 first countries and put them into 3 clusters based on the Wlaktrap algorithm:

- **Cluster 1**: China, Japan, South Korea, Israel, India, Greece, Singapore, New Zealand, Malaysia, United Arab Emirates, Thailand, South Africa, Saudi Arabia, Pakistan, Bangladesh
- **Cluster 2**: USA, Germany, United Kingdom, Canada, Italy, France, Australia, Netherlands, Spain, Switzerland, Belgium, Finland, Denmark, Iran, Brazil, Norway, Hungary, Ireland, Poland, Austria, Portugal, Russia, Sweden, Turkey, Czech Republic, Lithuania, Mexico, Slovenia, Estonia, Serbia, Cuba, Luxembourg
- **Cluster 3**: Chile, Argentina, Colombia

 doi:10.20944/preprints202310.0940.v1

3.4. Documents

According to Table 3, "Global Citations (TC) means the Total Citations that an article, included in your collection, has received from documents indexed on a bibliographic database (WoS, Scopus, etc.).", the applications such as FieldTrip [2], Brainstrom [41], ERPLAB [3] and MNE-Python [42] have the highest total citations. [35]

Table 3. The Most Global Cited Documents.

Row	Ref	Description	Total Citations	TC per Year	Normalized TC
1	[2]	FieldTrip app	5,427	417.46	59.16
2	[41]	Brainstorm app	1,924	148.00	20.97
3	[3]	ERPLAB app	1,422	142.20	34.99
4	[42]	MNE-Python	1,099	99.91	25.83
5	[43]	ICA – artifacts	1,087	63.94	12.35
6	[44]	Event-related potentials	1,014	50.70	6.19
7	[45]	Video game training	934	84.91	21.95
8	[46]	MNE Processing	887	88.70	21.83
9	[47]	EEGNet Model	853	142.17	40.13
10	[48]	Coupling , EEG-fMRI	837	44.05	6.01

According to Table 4, local citations are "the citations that a reference has received from documents included in your collection" [35], local to global ratio is above 50% for the ERPLAB app [3], ADJUST app [49], ICLabel app [4] and ICA and Blind Source Separation (BSS) [50].

Table 4. The Most Local Cited Documents.

Row	Ref	Description	Publication Year	Citations Local	Global	Ratio
1	[3]	ERPLAB app	2014	1215	1422	85.4
2	[49]	ADJUST app	2011	529	812	65.1
3	[43]	ICA – Artifacts Detection	2007	524	1087	48.2
4	[44]	ERP	2004	487	1014	48.0
5	[4]	ICLabel app	2019	392	501	78.2
6	[50]	ICA and BSS	2012	311	536	58.0
7	[51]	multiple comparison correction	2011	296	716	41.3
8	[48]	Coupling EEG/fMRI	2005	233	837	27.8
9	[52]	log spectral ICA	2005	229	590	38.8
10	[53]	ERP - Theta band	2012	172	428	40.2

According to Table 5, the most locally cited references are EEGLAB [1], FieldTrip[2] and Nonparametric statistical tests [54].

Table 5. Most Local Cited References.

Row	Ref	Description	Total Citations
1	[1]	EEGLAB	12,700
2	[2]	FieldTrip	1,507
3	[54]	Nonparametric statistical tests	1,267
4	[3]	ERPLAB	1,215
5	[55]	ERP – P300 (P3a , P3b)	1,046
6	[56]	Handedness analysis	970
7	[57]	blind separation and deconvolution	914
8	[58]	Artifacts - blind source separation	837
9	[59]	ERP/ MEG synchronization and desynchronization	831

10	[60]	Psychophysics Toolbox	797

The Reference Publication Year Spectroscopy (RPYS) [61] is presented in the supplementary. The years before 1900 are omitted because the number of them is very neglect. The peak at 2004 is related to the [1] with about 32.4% of all 39,155 references in 2004. And the highest peaks is in 2012 and 2014 with 40,360 and 40,431 references, respectively. The decline in the graph shows after 2014.

The trend topic of keyword plus is plotted. (Figure 3) The *dynamic*, *EEG* and *brain* terms have the highest frequency in 2019, while *safety*, *mini-mental state* and *attentional capture* term have the highest frequency in 2022.

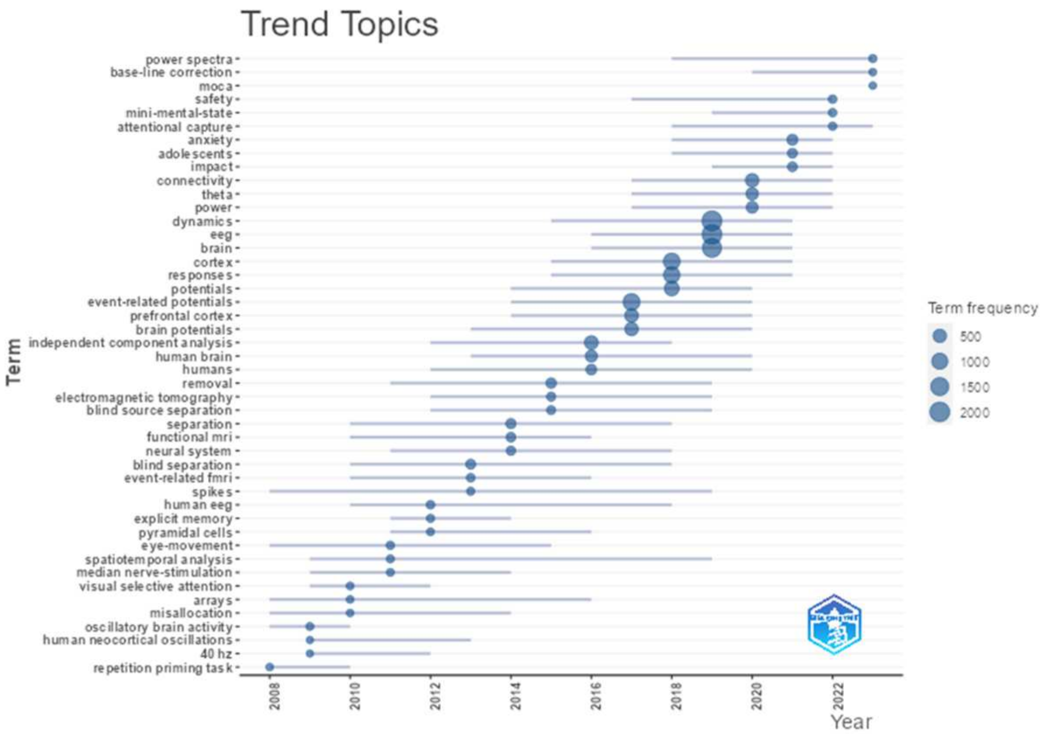

Figure 3. The trend topic plot of keyword plus.

The thematic map [62,63] of trigram words in abstracts is presented in Figure 4. It has four parts: 1) Niche themes (low centrality and high density, limited importance) including Alternating Current Stimulation (tACS), Transcranial Current Stimulation (tDCS) and Rapid serial visual presentation (RSVP). 2) Emerging or declined themes (low centrality and low density, marginal) including Local Field Potential (LFP) and Deep brain stimulation. 3) Motor Themes (high centrality and high density, important for research) including Transcranial magnetic stimulation (TMS), Alzheimer diseases, mild cognitive impairment (MCI)and delta, theta, alpha. 4) Basic Themes (high centrality and low density, general topics) including Independent Component Analysis (ICA), Magnetic Resonance Imaging (MRI), Brain Computer Interface (BCI), Support Vector Machine (SVM), Event Related potential (ERP) and Mismatch negativity (MMN).

 doi:10.20944/preprints202310.0940.v1

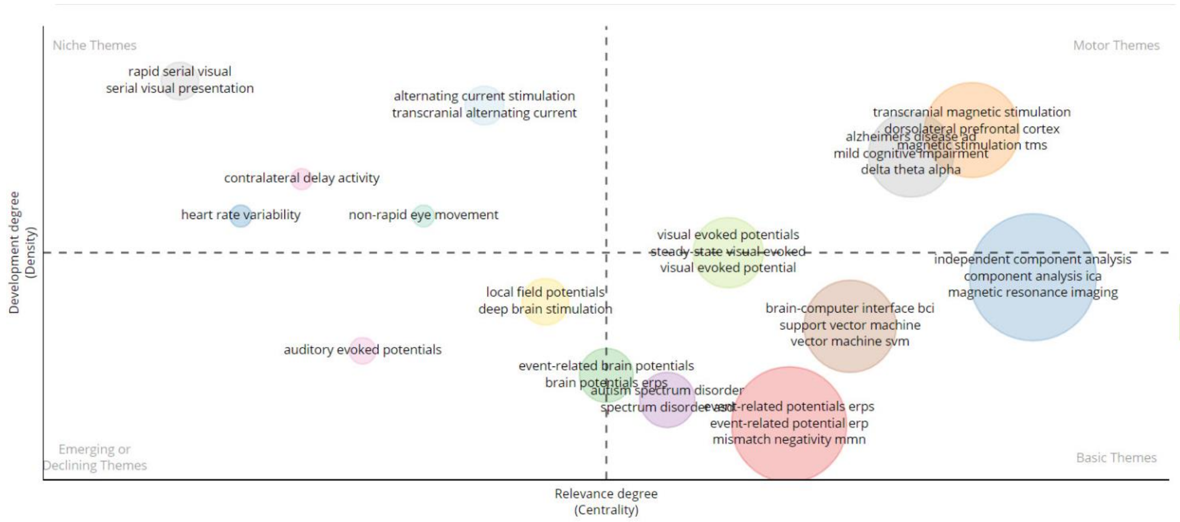

Figure 4. Thematic Map Trigram Word in Abstract.

The co-citation network between authors shows the relationship between cited sources in the documents in two populations: 1) All sources in Figure 5 and Table 6 show three clusters. Dr. Arnaud Delorme is in the center of the authors. 2) Core sources based on the Bradford Law Zone (n = 4318) in Figure 6. It has 7 clusters with Dr. Scott Makeig and Dr. Arnaud Delorme in one cluster, Dr. Stefan Debener in other clusters and Dr. Mike X Cohen in another cluster. The other remaning clusters are shown in Figure 6.

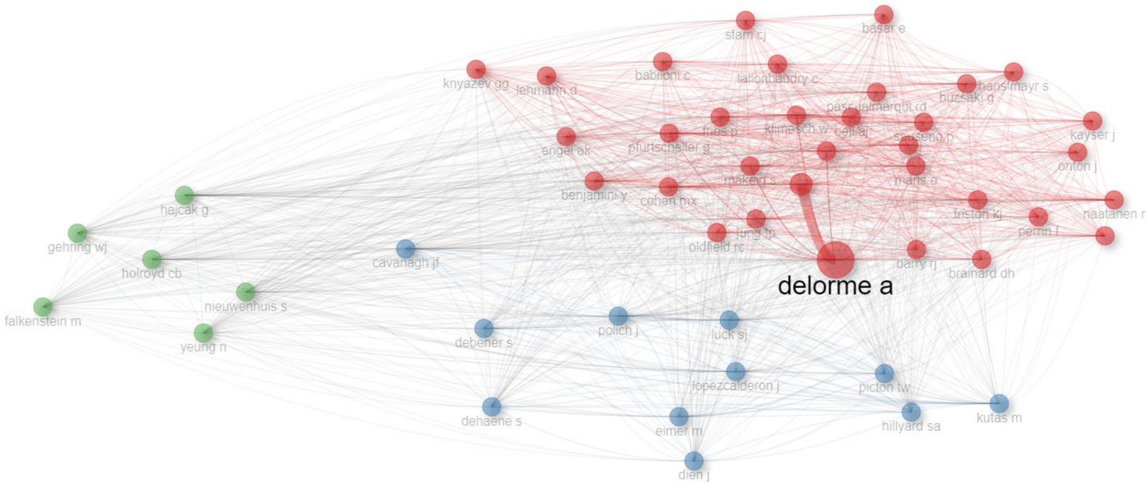

Figure 5. Co-Citation Network of Authors (3 Clusters).

Table 6. Co-Citation Network.

Row	Clusters	Author Name (last Name, abbreviated First Name)
1	1	delorme a, anonymous, klimesch w, pfurtscheller g, makeig s, oostenveld r, cohen mx, naatanen r, jung tp, maris e, jensen o, pascualmarqui rd, friston kj, benjamini y, buzsaki g, sauseng p, oldfield rc, bell aj, babiloni c, winkler i , tallonbaudry c, brainard dh, fries p, hanslmayr s, stam cj, onton j, engel ak, perrin f, kayser j, basar e, barry rj, knyazev gg, lehmann d
2	2	luck sj, polich j, kutas m, lopezcalderon j, cavanagh jf, eimer m, debener s, picton tw, dien j, dehaene s, hillyard sa
3	3	hajcak g, holroyd cb, nieuwenhuis s, yeung n, falkenstein m, gehring wj

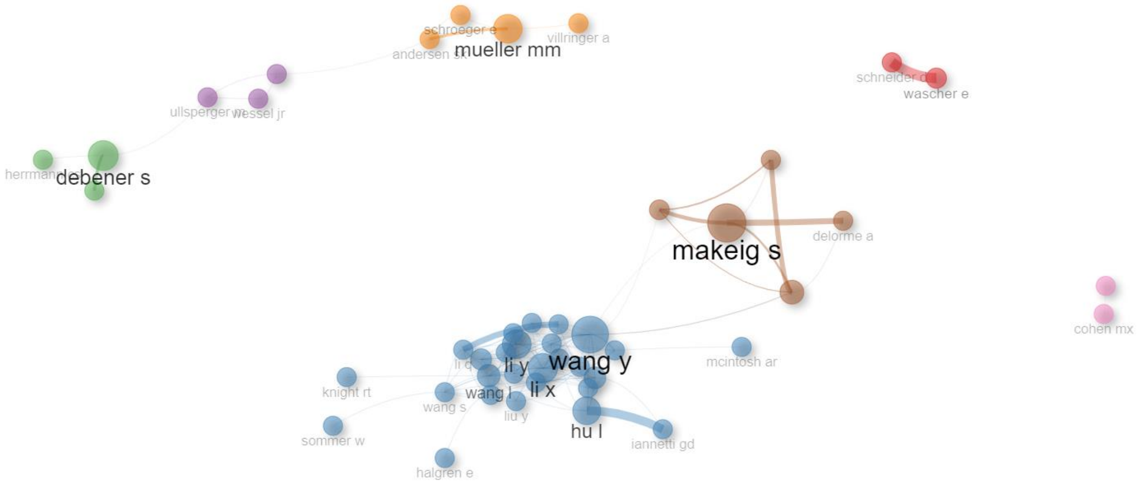

Figure 6. Co-Citation Network of Authors (7 Clusters) Core Sources – Bradford Law Zone (n = 4318).

4. Conclusions

Despite the emerging and the growth of open source Python and related MNE library [42] for computational neuroscience (with more than 2,000 Google citations), EEGLAB has the highest number of google citations among similar software like SPM [64] (with more than 11,000 Google citations). Many global and famous universities and research institutes published research with EEGLAB in the USA, Europe, Canada, Japan, Australia and Russia. But it is not limited to developed countries, and many developing countries like China, India, Taiwan, Turkey, Iran, Saudi Arabia, Bangladesh, Brazil, Cuba, Argentina, Colombia, and many others use it in their scientific experiments and publications.

One of the main limitations of this research is that it only considers the ISI-indexed articles. Still, due to the large number of research articles, it covers many important aspects of literature. The second limitation is that it is not about all computational neuroscience papers, but it is only about the papers that cited the EEGLAB and with a high probability have EEG datasets. For example, tDSC and tACS have existed in the niche theme of Figure 4, but they are growing topics in the neuroscience literature. [65,66]. The one direction for future research is bibliographic analysis of special statistical methods with EEGLAB and EEG datasets for example, machine learning methods such as support vector machine [67], dimension reduction methods such as ICA [43] , functional data analysis methods [68,69], and deep learning methods [17,70].

Further analysis including world clouds, tree maps, bar charts of the most frequent words in keywords plus, keyword, title (unigram, bigram, trigram) and abstract (unigram, bigram, trigram) and many others are presented in the Supplementary Materials.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org. It has two supplementary: 1) Further Analysis and 2) the bib file for reproducing results (~ size: 100 mb).

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

References

1. Delorme, A. and S. Makeig, *EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis.* Journal of neuroscience methods, 2004. **134**(1): p. 9-21.
2. Oostenveld, R., et al., *FieldTrip: open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data.* Computational intelligence and neuroscience, 2011. **2011**: p. 1-9.
3. Lopez-Calderon, J. and S.J. Luck, *ERPLAB: an open-source toolbox for the analysis of event-related potentials.* Frontiers in human neuroscience, 2014. **8**: p. 213.

4. Pion-Tonachini, L., K. Kreutz-Delgado, and S. Makeig, *ICLabel: An automated electroencephalographic independent component classifier, dataset, and website.* NeuroImage, 2019. **198**: p. 181-197.
5. Delorme, A., et al., *EEGLAB, SIFT, NFT, BCILAB, and ERICA: new tools for advanced EEG processing.* Computational intelligence and neuroscience, 2011. **2011**: p. 10-10.
6. Palmer, J.A., K. Kreutz-Delgado, and S. Makeig, *AMICA: An adaptive mixture of independent component analyzers with shared components.* Swartz Center for Computatonal Neursoscience, University of California San Diego, Tech. Rep, 2012.
7. Miyakoshi, M., et al. *Automated detection of cross-frequency coupling in the electrocorticogram for clinical inspection*. in *2013 35th Annual International Conference of the Ieee Engineering in Medicine and Biology Society (Embc)*. 2013. IEEE.
8. Pernet, C.R., et al., *LIMO EEG: a toolbox for hierarchical LInear MOdeling of ElectroEncephaloGraphic data.* Computational intelligence and neuroscience, 2011. **2011**: p. 1-11.
9. Friston, K.J., *Statistical parametric mapping.* Neuroscience databases: a practical guide, 2003: p. 237-250.
10. Blankertz, B., et al., *The Berlin brain-computer interface: progress beyond communication and control.* Frontiers in neuroscience, 2016. **10**: p. 530.
11. Kothe, C.A. and S. Makeig, *BCILAB: a platform for brain–computer interface development.* Journal of neural engineering, 2013. **10**(5): p. 056014.
12. Muschelli, J., et al., *Neuroconductor: an R platform for medical imaging analysis.* Biostatistics, 2019. **20**(2): p. 218-239.
13. Tran, X.A., et al., *Functional connectivity during language processing in 3-month-old infants at familial risk for autism spectrum disorder.* European Journal of Neuroscience, 2021. **53**(5): p. 1621-1637.
14. Schirner, M., et al., *An automated pipeline for constructing personalized virtual brains from multimodal neuroimaging data.* NeuroImage, 2015. **117**: p. 343-357.
15. An, S., et al., *High-resolution virtual brain modeling personalizes deep brain stimulation for treatment-resistant depression: Spatiotemporal response characteristics following stimulation of neural fiber pathways.* NeuroImage, 2022. **249**: p. 118848.
16. Broyd, S.J., et al., *Default-mode brain dysfunction in mental disorders: a systematic review.* Neuroscience & biobehavioral reviews, 2009. **33**(3): p. 279-296.
17. Craik, A., Y. He, and J.L. Contreras-Vidal, *Deep learning for electroencephalogram (EEG) classification tasks: a review.* Journal of neural engineering, 2019. **16**(3): p. 031001.
18. Jenke, R., A. Peer, and M. Buss, *Feature extraction and selection for emotion recognition from EEG.* IEEE Transactions on Affective computing, 2014. **5**(3): p. 327-339.
19. Sonuga-Barke, E.J., et al., *Nonpharmacological interventions for ADHD: systematic review and meta-analyses of randomized controlled trials of dietary and psychological treatments.* American journal of psychiatry, 2013. **170**(3): p. 275-289.
20. Ismail, L.E. and W. Karwowski, *Applications of EEG indices for the quantification of human cognitive performance: A systematic review and bibliometric analysis.* Plos one, 2020. **15**(12): p. e0242857.
21. Wijaya, A., et al., *Electroencephalography and mild cognitive impairment research: A scoping review and bibliometric analysis (ScoRBA).* AIMS neuroscience, 2023. **10**(2): p. 154.
22. Chen, X.-X., et al., *Bibliometric analysis of the effects of mental fatigue on athletic performance from 2001 to 2021.* Frontiers in Psychology, 2023. **13**: p. 1019417.
23. Yao, S., et al., *Bibliometric analysis of quantitative electroencephalogram research in neuropsychiatric disorders from 2000 to 2021.* Frontiers in Psychiatry, 2022. **13**: p. 830819.
24. Alsharif, A., et al., *Current Trends in the Application of EEG in Neuromarketing: A Bibliometric Analysis.* Scientific Annals of Economics and Business, 2022. **69**(3): p. 393-415.
25. Alsharif, A.H., et al., *Neuromarketing research in the last five years: A bibliometric analysis.* Cogent Business & Management, 2021. **8**(1): p. 1978620.
26. Liu, Y., et al., *A Bibliometric Analysis of Consumer Neuroscience towards Sustainable Consumption.* Behavioral Sciences, 2023. **13**(4): p. 298.
27. Costa-Feito, A., et al., *Electroencephalography in consumer behaviour and marketing: a science mapping approach.* Humanities and Social Sciences Communications, 2023. **10**(1): p. 1-13.
28. Radtke Caneppele, N., et al., *Potential and challenges for using neuroscientific tools in strategic management studies.* RAUSP Management Journal, 2022. **57**: p. 235-263.
29. Tsiamalou, A., et al., *EEG in neurorehabilitation: a bibliometric analysis and content review.* Neurology International, 2022. **14**(4): p. 1046-1061.
30. Ghamari, H., et al., *Neuroarchitecture assessment: an overview and bibliometric analysis.* European Journal of Investigation in Health, Psychology and Education, 2021. **11**(4): p. 1362-1387.
31. Saedi, S., et al., *Applications of electroencephalography in construction.* Automation in Construction, 2022. **133**: p. 103985.
32. Kontoghiorghes, L. and A. Colubi, *New metrics and tests for subject prevalence in documents based on topic modeling.* International Journal of Approximate Reasoning, 2023. **157**: p. 49-69.

33. Winker, P., *Visualizing Topic Uncertainty in Topic Modelling.* arXiv preprint arXiv:2302.06482, 2023.
34. Chen, X., et al., *Global research on artificial intelligence-enhanced human electroencephalogram analysis.* Neural Computing and Applications, 2022: p. 1-39.
35. Aria, M. and C. Cuccurullo, *bibliometrix: An R-tool for comprehensive science mapping analysis.* Journal of informetrics, 2017. **11**(4): p. 959-975.
36. Team, R.D.C., *R: A language and environment for statistical computing.* (No Title), 2010.
37. Bornmann, L. and H.D. Daniel, *What do we know about the h index?* Journal of the American Society for Information Science and technology, 2007. **58**(9): p. 1381-1385.
38. Egghe, L., *Theory and practise of the g-index.* Scientometrics, 2006. **69**(1): p. 131-152.
39. Bornmann, L., R. Mutz, and H.D. Daniel, *Are there better indices for evaluation purposes than the h index? A comparison of nine different variants of the h index using data from biomedicine.* Journal of the American Society for Information Science and technology, 2008. **59**(5): p. 830-837.
40. Pons, P. and M. Latapy, *Computing communities in large networks using random walks.* J. Graph Algorithms Appl., 2006. **10**(2): p. 191-218.
41. Tadel, F., et al., *Brainstorm: a user-friendly application for MEG/EEG analysis.* Computational intelligence and neuroscience, 2011. **2011**: p. 1-13.
42. Gramfort, A., et al., *MEG and EEG data analysis with MNE-Python.* Frontiers in neuroscience, 2013: p. 267.
43. Delorme, A., T. Sejnowski, and S. Makeig, *Enhanced detection of artifacts in EEG data using higher-order statistics and independent component analysis.* Neuroimage, 2007. **34**(4): p. 1443-1449.
44. Makeig, S., et al., *Mining event-related brain dynamics.* Trends in cognitive sciences, 2004. **8**(5): p. 204-210.
45. Anguera, J.A., et al., *Video game training enhances cognitive control in older adults.* Nature, 2013. **501**(7465): p. 97-101.
46. Gramfort, A., et al., *MNE software for processing MEG and EEG data.* neuroimage, 2014. **86**: p. 446-460.
47. Lawhern, V.J., et al., *EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces.* Journal of neural engineering, 2018. **15**(5): p. 056013.
48. Debener, S., et al., *Trial-by-trial coupling of concurrent electroencephalogram and functional magnetic resonance imaging identifies the dynamics of performance monitoring.* Journal of Neuroscience, 2005. **25**(50): p. 11730-11737.
49. Mognon, A., et al., *ADJUST: An automatic EEG artifact detector based on the joint use of spatial and temporal features.* Psychophysiology, 2011. **48**(2): p. 229-240.
50. Delorme, A., et al., *Independent EEG sources are dipolar.* PloS one, 2012. **7**(2): p. e30135.
51. Groppe, D.M., T.P. Urbach, and M. Kutas, *Mass univariate analysis of event-related brain potentials/fields I: A critical tutorial review.* Psychophysiology, 2011. **48**(12): p. 1711-1725.
52. Onton, J., A. Delorme, and S. Makeig, *Frontal midline EEG dynamics during working memory.* Neuroimage, 2005. **27**(2): p. 341-356.
53. Cavanagh, J.F., L. Zambrano-Vazquez, and J.J. Allen, *Theta lingua franca: A common mid-frontal substrate for action monitoring processes.* Psychophysiology, 2012. **49**(2): p. 220-238.
54. Maris, E. and R. Oostenveld, *Nonparametric statistical testing of EEG-and MEG-data.* Journal of neuroscience methods, 2007. **164**(1): p. 177-190.
55. Polich, J., *Updating P300: an integrative theory of P3a and P3b.* Clinical neurophysiology, 2007. **118**(10): p. 2128-2148.
56. Oldfield, R.C., *The assessment and analysis of handedness: the Edinburgh inventory.* Neuropsychologia, 1971. **9**(1): p. 97-113.
57. Bell, A.J. and T.J. Sejnowski, *An information-maximization approach to blind separation and blind deconvolution.* Neural computation, 1995. **7**(6): p. 1129-1159.
58. Jung, T.-P., et al., *Removing electroencephalographic artifacts by blind source separation.* Psychophysiology, 2000. **37**(2): p. 163-178.
59. Pfurtscheller, G. and F.L. Da Silva, *Event-related EEG/MEG synchronization and desynchronization: basic principles.* Clinical neurophysiology, 1999. **110**(11): p. 1842-1857.
60. Brainard, D.H. and S. Vision, *The psychophysics toolbox.* Spatial vision, 1997. **10**(4): p. 433-436.
61. Marx, W., et al., *Detecting the historical roots of research fields by reference publication year spectroscopy (RPYS).* Journal of the Association for Information Science and Technology, 2014. **65**(4): p. 751-764.
62. Aria, M., M. Misuraca, and M. Spano, *Mapping the evolution of social research and data science on 30 years of social indicators research.* Social indicators research, 2020. **149**: p. 803-831.
63. Aria, M., et al., *Thematic analysis as a new culturomic tool: the social media coverage on COVID-19 pandemic in Italy.* Sustainability, 2022. **14**(6): p. 3643.
64. Friston, K.J., et al., *Statistical parametric maps in functional imaging: a general linear approach.* Human brain mapping, 1994. **2**(4): p. 189-210.
65. Day, P., J. Twiddy, and V. Dubljević, *Present and emerging ethical issues with tDCS use: A summary and review.* Neuroethics, 2023. **16**(1): p. 1.

 doi:10.20944/preprints202310.0940.v1

66. Manippa, V., et al., *Cognitive and neuropathophysiological outcomes of gamma-tACS in dementia: a systematic review.* Neuropsychology Review, 2023: p. 1-24.
67. Hastie, T., et al., *The elements of statistical learning: data mining, inference, and prediction*. Vol. 2. 2009: Springer.
68. Scheffler, A., et al., *Hybrid principal components analysis for region-referenced longitudinal functional EEG data.* Biostatistics, 2020. **21**(1): p. 139-157.
69. Ramsay, J. and B. Silverman, *Functional Data Analysis*. 2 ed. 2005: Springer New York, NY.
70. Schirrmeister, R.T., et al., *Deep learning with convolutional neural networks for EEG decoding and visualization.* Human brain mapping, 2017. **38**(11): p. 5391-5420.