Journal of Multidisciplinary Healthcare

Dovepress
Taylor & Francis Group

Open Access Full Text Article

ORIGINAL RESEARCH

A Bibliometric Analysis of the Application of Brain-Computer Interface in Rehabilitation Medicine Over the Past 20 Years

Jinghui Huang[1,*], Lele Huang[2,*], Ying Li[1,*], Fanfu Fang[1]

[1]Department of Rehabilitation Medicine, The First Affiliated Hospital of the Naval Medical University, Shanghai, 200433, People's Republic of China; [2]Department of Sports Medicine, Peking University Third Hospital, Institute of Sports Medicine of Peking, Beijing, 100191, People's Republic of China

*These authors contributed equally to this work

Correspondence: Fanfu Fang, Email fangfanfu@126.com

Objective: This study aims to conduct a bibliometric analysis of the application of brain- computer interface (BCI) in rehabilitation medicine, assessing the current state, developmental trends, and future potential of this field. By systematically analyzing relevant literature, we seek to identify key research themes and enhance understanding of BCI technology in rehabilitation.

Methods: We utilized bibliometric analysis tools such as VOSviewer and CiteSpace to screen and analyze 426 relevant articles from the Web of Science Core Collection (WoSCC) database. We quantitatively evaluated citation patterns, publication trends, and the collaboration networks of research institutions and authors to uncover research hotspots and frontier dynamics in the field.

Results: The findings indicate a continuous increase in research publications since 2003, with a notable peak occurring between 2019 and 2021. The analysis revealed that motor imagery, motor recovery, and signal processing are the predominant research themes. Furthermore, the United States and China are leading in the publication volume related to BCI and rehabilitation medicine. Key research institutions include the University of Tübingen and the New York State Department of Health, with significant contributions from scholars like Niels Birbaumer.

Conclusion: Although the current research on BCI in rehabilitation medicine shows significant potential and efficacy, further exploration of certain research directions is needed, along with the promotion of interdisciplinary collaboration to comprehensively address complex real-world issues such as motor function impairment. Future research should focus on optimizing training models, enhancing technical feasibility, and exploring home rehabilitation applications to facilitate the broader adoption of BCI technology in rehabilitation medicine.

Keywords: brain-computer interface, BCI, rehabilitation, motor recovery, motor imagery, signal processing

Introduction

In 1973, Professor Jacques J. Vidal from the University of California, Los Angeles (UCLA), coined the term "brain-computer interface" (BCI) and developed the world's first BCI system.[1] Since then, numerous researchers have devoted themselves to exploring and advancing this technology. While early progress was relatively slow, the rapid developments in neuroscience, neurobiology, and computer science have propelled BCI research into a period of significant breakthroughs over the past decade. In 2016, researchers at Johns Hopkins University School of Medicine created a robotic hand controlled by cortical brain signals. In September of the same year, Stanford University successfully used BCI technology to enable a monkey to type Shakespeare's classic lines.[2] By January 2024, Neuralink implanted its BCI chip into the first human patient. Currently, BCI technology plays a pivotal role in neuroscience and psychology, aiding in the exploration of brain functions and disease mechanisms, monitoring psychological states, and supporting therapeutic interventions. Moreover, it has found extensive applications in fields such as gaming, military, aerospace, smart homes,

Received: 21 December 2024
Accepted: 21 February 2025
Published: 4 March 2025

and education. These include providing immersive gaming experiences, assisting astronauts in operations, enhancing convenience in daily living, and improving educational outcomes.[3–5]

In today's fast-paced technological landscape, Brain-Computer Interface (BCI) technology has emerged as a groundbreaking innovation, particularly in the field of rehabilitation medicine. As an advanced form of human-computer interaction, BCI create a direct communication pathway between the brain and external devices by capturing and interpreting brain signals. This offers renewed hope and opportunities for patients with neurological injuries.[6]

The primary goal of rehabilitation medicine is to maximize the recovery of lost functions and improve patients' quality of life. BCI technology holds considerable promise in achieving these objectives. For example, stroke patients often experience significant motor impairments that severely impact their daily activities. Studies have shown that rehabilitation training incorporating BCI can substantially improve motor function recovery in stroke patients.[7] This suggests that BCI technology may facilitate the activation of damaged neural pathways, promoting neuroplasticity and functional recovery.[8] The team led by Meng Xia from Beijing Tiantan Hospital, Capital Medical University, published a study in Med, a Cell Press journal, in 2024. The study involved 296 ischemic stroke patients who were randomly assigned to a BCI group and a control group at a 1:1 ratio. From baseline to one month, the change in Fugl-Meyer Assessment for Upper Extremity Motor Function (FMA-UE) scores was 13.17 points in the BCI group and 9.83 points in the control group, with a mean difference of 3.35 points between the two groups.[9]

BCI technology has also made significant advancements for patients with spinal cord injuries. Such injuries can result in partial or complete loss of motor control. However, with BCI-controlled assistive devices, such as smart wheelchairs, patients can regain a degree of mobility.[10] In clinical trials, paralyzed patients have demonstrated fine motor control, such as grasping movements, using robotic neuroprostheses or neuromuscular stimulation orthoses controlled by intracortical BCI systems.[11] These innovations not only enhance patients' ability to perform daily activities but also boost their confidence and overall outlook on life.

BCI technology also plays a crucial role in the rehabilitation of patients with cognitive impairments. Cognitive disorders can affect various aspects of a patient's functioning, such as memory, attention, and reasoning. By monitoring brain activity, BCI systems can provide real-time insights into a patient's cognitive state, enabling precise assessments to guide rehabilitation strategies. The application of BCI in post-stroke cognitive impairment (PSCI) represents a novel approach in neurorehabilitation, with BCI being used for the assessment, training, and treatment of PSCI. Research has shown that BCI can help improve cognitive function in patients with PSCI.[12] By detecting neural activity, classifying and extracting relevant information, and decoding a subject's intentions, BCI systems can facilitate neural interactions through neurofeedback and motor imagery. Repeated training with BCI can alter synaptic potentials, enhance brain adaptability, improve functional connectivity within neural networks, and rebalance hemispheric interactions, promoting cortical reorganization through neuroplasticity and ultimately improving cognitive function.

The emerging trends in brain-computer interface (BCI) technology are rapidly advancing, with home-based rehabilitation models leveraging remote monitoring and guidance to enable patients to conveniently undergo rehabilitation training at home.[13] This approach overcomes the constraints of time and space, improving rehabilitation efficiency and quality of life. Simultaneously, the integration of artificial intelligence enables precise analysis of EEG signals, optimizing rehabilitation strategies. Wearable devices, characterized by portability, comfort, and ease of use, further expand the application scenarios of BCI.[14] Despite its promising potential in the rehabilitation field, BCI technology still faces significant challenges. Issues such as low signal acquisition precision, inefficient data processing, limited stability, high equipment costs, poor usability, inadequate comfort, complex operation, and compatibility limitations remain prominent.[15–18] Ethical challenges are also a critical concern, including severe privacy risks and difficulties in defining intervention boundaries. In clinical applications, the scope of applicable conditions is limited, successful cases are relatively rare, and the lack of standardized protocols further restricts its widespread adoption.[19,20] Addressing these barriers is essential to unlocking the full potential of BCIs in rehabilitation.

In recent years, the integration of neuroscience, engineering, and other disciplines has fueled rapid advancements in the application of BCI for rehabilitation medicine.[21] A growing number of research teams are dedicating efforts to this field, exploring new technologies, methods, and applications.[22] However, bibliometric analyses of this research area are still relatively limited, making it challenging to fully understand its current state, key areas of focus, and emerging trends.

Therefore, this study aims to conduct a systematic bibliometric analysis of the literature on BCI applications in rehabilitation medicine. By using VOSviewer or CiteSpace, functions such as keyword co-occurrence, co-citation analysis, author and institutional collaboration analysis, clustering, and burst term detection can be employed to identify research trends, analyze collaboration models, and detect knowledge gaps, thereby enhancing the rationality and innovativeness of research. By uncovering critical insights, this analysis seeks to provide valuable scientific references and guidance for further research, promoting the broader application and deeper development of BCI technology in rehabilitation medicine.

Methods

Search Strategy and Data Collection

The literature reviewed in this study was collected from the Web of Science (WOS) database, a highly authoritative academic resource platform that holds a prominent position in the global academic community.[23] WOS encompasses a broad range of disciplines, including natural sciences, social sciences, humanities, and arts, and aggregates top-tier academic journals, authoritative conference papers, and valuable book chapters from around the world.[24] The database offers powerful and precise search capabilities, enabling users to efficiently retrieve relevant literature through various search filters, such as keywords, authors, institutions, and publication years.[25] Whether tracking the latest developments in a specific research field or searching for the academic contributions of a prominent scholar, WOS provides a highly efficient service. Additionally, WOS offers a variety of analysis tools and metrics, such as impact factor and citation frequency, to help researchers quickly identify cutting-edge developments, research hotspots, and emerging trends, supporting academic research and innovation.[26]

WOS is also equipped with an extensive suite of literature analysis tools. Citation frequency statistics provide an intuitive measure of a paper's impact in the academic community, while co-citation analysis helps researchers gain insights into the knowledge structure and evolution of a specific field. These tools enable researchers to better understand research trends, identify potential collaboration opportunities, and strengthen their own research efforts. With its comprehensive coverage, robust search capabilities, and specialized analytical tools, WOS continues to serve as an indispensable resource for researchers worldwide, driving academic progress across disciplines.

Data Collection Process

For this study, we conducted a systematic search of publications indexed in the Web of Science Core Collection (WOSCC) from January 2003 to January 31, 2024. The search strategy was as follows: ((((TI=(brain-computer interface)) OR TI=(brain-machine interface)) OR TI=(brain-computer interfaces)) OR TI=(brain-machine interfaces)) AND TS=(rehabilitation), with the document types limited to articles and review articles. This search yielded a total of 426 publications. The retrieved documents were then subjected to a bibliometric analysis based on inclusion and exclusion criteria. The inclusion criteria were as follows: (1) publications dated between January 1, 2003, and January 31, 2024; (2) only articles and review articles; and (3) content focused on the application of BCI in rehabilitation medicine. The exclusion criteria were: (1) duplicate publications, and (2) non-article documents, such as book reviews, notices, editorials, conference abstracts, conference papers, and letters.

Two authors independently categorized the extracted data. In the case of any disagreement, a third reviewer was consulted to reach a consensus. During the data processing phase, we focused on duplicate record cleaning and the standardization of key information. After completing the literature search, the data were imported into EndNote, where the duplicate detection function was used to automatically identify and remove duplicate records based on key details such as title, author, publication year, and journal name. Manual inspection was then performed to eliminate duplicates overlooked by the software. For inconsistencies in author names, affiliations, and keywords, preliminary standardization was conducted using reference management software. Specifically, author names were manually consolidated by reviewing their research areas, related publications, and institutional affiliations. For affiliations, discrepancies were corrected and verified using an institution name reference list, search engines, and official websites. Regarding keywords, a standardized terminology was established through the construction of a synonym database, incorporating authoritative

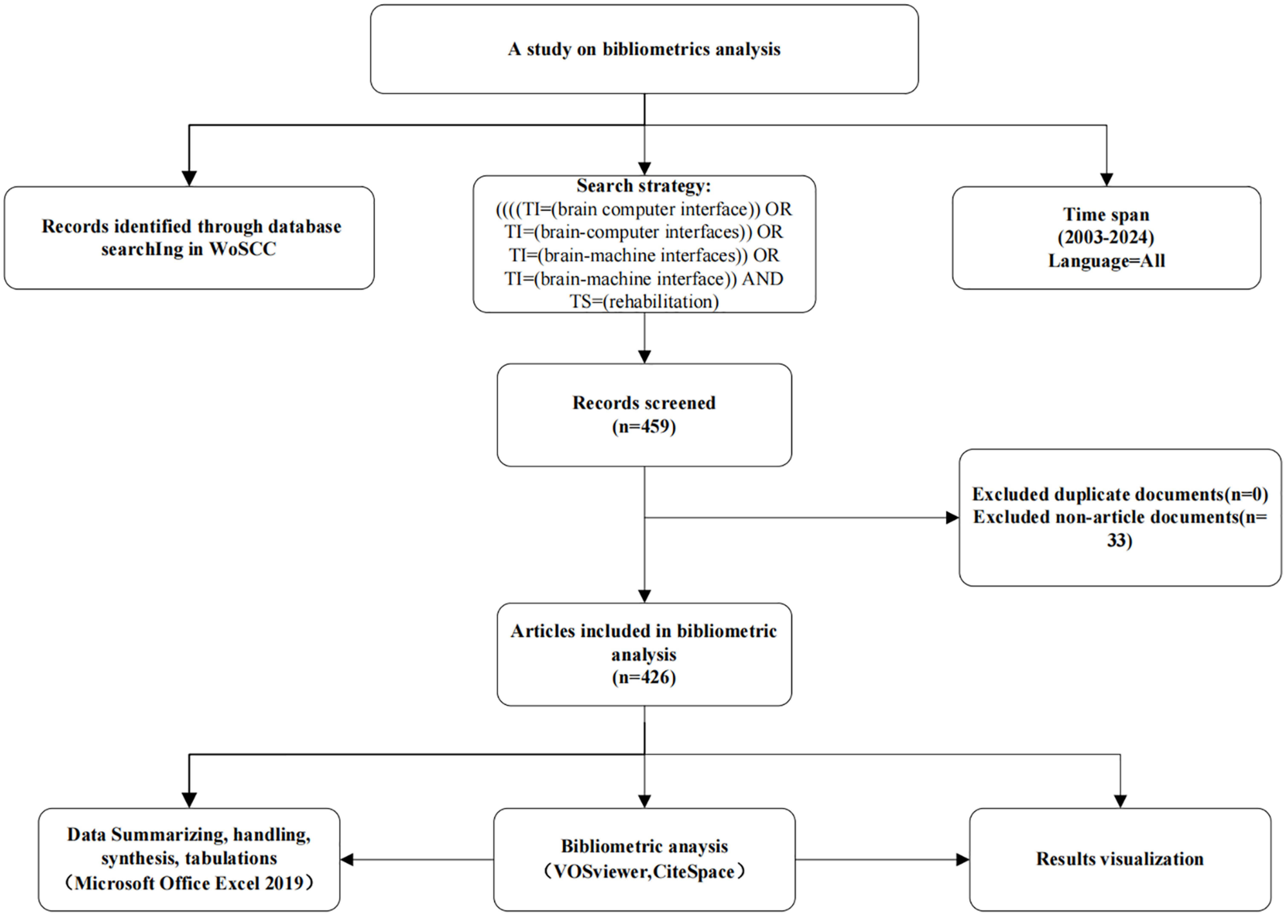

Figure 1 Flowchart of this study.

literature and expert opinions to address special cases. As of January 31, 2024, a total of 426 publications were successfully retrieved from the specified database. The workflow for literature search and analysis is detailed in Figure 1.

In total, 426 papers were included in this study. These records were exported as plain text files, with the export format containing "complete records and cited references", and the files were saved in "download_txt" format.

Knowledge Visualization Analysis

In this study, VOSviewer, CiteSpace, and Microsoft Excel 2021 were employed for quantitative and visual analyses. VOSviewer[27] is a tool designed to extract key information from large sets of publications and is used to construct networks of collaboration, co-citation, and co-occurrence. In these networks, node size represents the number of publications, line width reflects the strength of relationships, and node color indicates different clusters or time periods. VOSviewer provides various visualization modes, such as network and density views, and can distinguish clusters or nodes using different colors. Its functions include literature clustering analysis, which allows for a rapid understanding of research directions and topics; collaboration network analysis, which promotes cooperation between authors and institutions; and keyword analysis, revealing core concepts and research hotspots.

CiteSpace[28] offers powerful visualization capabilities, displaying bibliometric relationships through various graphs, such as keyword co-occurrence and author collaboration maps. It supports dynamic analysis and the import of data from multiple databases. CiteSpace can identify research hotspots by analyzing keyword co-occurrence and detecting frequently appearing terms. It also reveals the knowledge structure of a field by examining citation relationships and constructing knowledge maps. In addition, it helps identify research frontiers by highlighting emerging keywords and highly cited papers. Keywords or references that show a sudden increase in frequency over time indicate topics that have garnered significant attention from researchers, and these "bursts" are considered indicators of research hotspots or frontiers.[29]

By utilizing these tools, we effectively identified key themes, recent developments, and emerging trends in the field. VOSviewer (version 1.6.19) and CiteSpace (version 6.2.R2) were used to visualize and analyze the relevant literature on the application of BCI in rehabilitation medicine from the WOSCC database. The knowledge maps generated from this analysis provided insights into the research landscape, helping to pinpoint research hotspots and development trends in this field. This analysis serves as a valuable reference for guiding future research, offering researchers insights into evolving research dynamics and helping them avoid redundancy. Additionally, it fosters academic exchange and collaboration by identifying potential partners, provides decision-making support for research management by highlighting the current state of the field, and facilitates resource allocation. By uncovering gaps and underexplored areas, this analysis also drives the advancement of the discipline, offering guidance for future development and innovation.

These software tools deliver valuable information and insights for researchers, supporting the growth of academic research in the field of BCI applications in rehabilitation medicine.

Results

Publication Trends

From 2003 to 2024, a total of 463 publications were identified, including 426 articles and review papers, with the majority being original research articles. These articles and reviews collectively cited 23,285 references, averaging 54.66 citations per publication. Overall, the number of publications has shown a growing trend, as depicted in Figure 2. In 2023, the average number of citations per paper in the WoSCC database was 4.35, compared to 183.5 citations per paper in 2003. In 2023, 52 papers were published, accumulating 226 total citations. The number of publications and citations per year reflects both research trends and the impact of work in this field.

Notably, 221 articles, or 51.88% of the total, were published in the last five years, indicating that BCI is an emerging technology that has developed rapidly and garnered increasing global attention in recent years. The growth in the number of publications in this field has followed an approximately exponential trend, with the predicted model formula being $y = 1.1644^{\times 1.0611}$, where y represents the number of publications, and X represents the year. The R^2 value of 0.6268 suggests

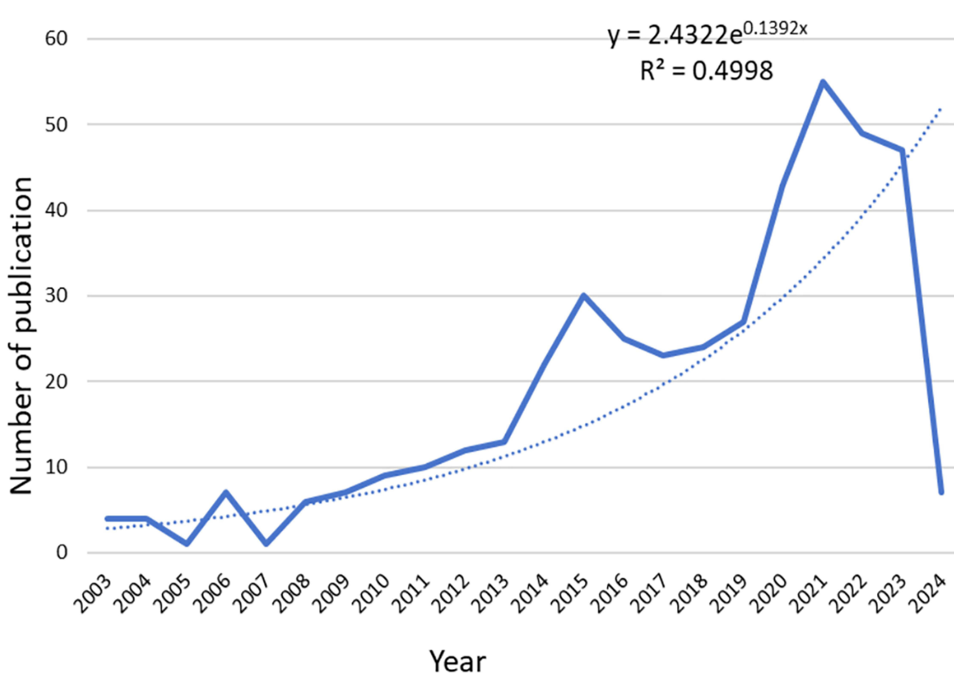

Figure 2 Annual publication outputs and growth prediction from 2003 to 2022.

a good fit of the curve to the data. This indicates that the field of BCI has established a solid research foundation and continues to attract significant interest from researchers.

Regional Trends

A bibliometric analysis of publication output by country (Table 1) reveals that the United States leads in the number of publications related to BCI and rehabilitation medicine over the past 20 years. China ranks second in publication volume, with 1,421 citations and an average citation rate of 23.52 per paper. Australia has the earliest average publication time, indicating that research in this area began earlier in Australia compared to other countries. In contrast, China has the latest average publication time, suggesting that research efforts in this field have intensified only in recent years. However, the volume and impact of Chinese publications have grown significantly.

The United States ranks first in total citations, with 10,547, followed by Germany with 6,991 citations. Italy has the highest average citation rate, at 135.71 per paper, indicating that research from these countries has garnered considerable attention. A comprehensive analysis of publication volume, link strength, citation count, and average citations demonstrates that the United States holds a dominant position in this field.

Figure 3 illustrates the country/region collaboration network, where each node represents a country or region, and the lines between nodes indicate collaborative relationships. The thickness of the lines reflects the strength of collaboration, with Total Link Strength (TLS) representing the intensity of cooperation. From both the figure and table, it is clear that Germany and the United States exhibit the highest collaboration intensity.

Institutional Publication Analysis

The co-authorship network for institutions (Figure 4) provides an overview of the publication landscape for various research institutions involved in brain-computer interface (BCI) studies related to rehabilitation. The visualization highlights institutions with significant contributions, where node size corresponds to the number of publications, line width indicates the strength of collaborative relationships, and node color represents different clusters or time periods.

The analysis reveals that 63 institutions have published more than three papers each, collectively accounting for 329 publications, which represents 77.23% of the total literature. Table 2 lists the 10 institutions with the highest number of publications. The top 10 institutions in terms of publication volume have contributed 114 articles, making up 26.76% of all publications in this field. The leading institutions are primarily located in Germany, China, the United States, Japan, Italy, and Austria. Among the top 10, Chinese institutions are the most represented, with three institutions making the list.

The University of Tübingen holds the top position in terms of publication volume, with 26 papers and a total of 5,033 citations, ranking second in total citations among institutions. The second-highest in publication volume is the New York State Department of Health, which has published 13 papers but ranks first in total citations, with 5,099 citations, indicating the significant impact of its research.

Table 1 Top 10 Countries Based on the Total Number of Publications for 2003 to 2024

Country	Publications	Citations	Avg. Citations	Avg. Pub. Year	TLS
United States	102	10,547	103.402	2015.569	80
China	98	2305	23.5204	2020.469	33
Germany	56	6991	124.8393	2015.018	81
Italy	41	5564	135.7073	2016.268	47
Spain	32	3599	112.4688	2016.594	46
United Kingdom	30	1483	49.4333	2018.367	33
Japan	22	792	36	2017.5	20
South Korea	22	963	43.7727	2017.818	9
Austria	17	2131	125.3529	2012.941	31
Canada	17	626	36.8235	2019.529	17

Abbreviations: Avg. Citations, Average citations; Avg. Pub. Year, Average publication Year; TLS, Total link strength.

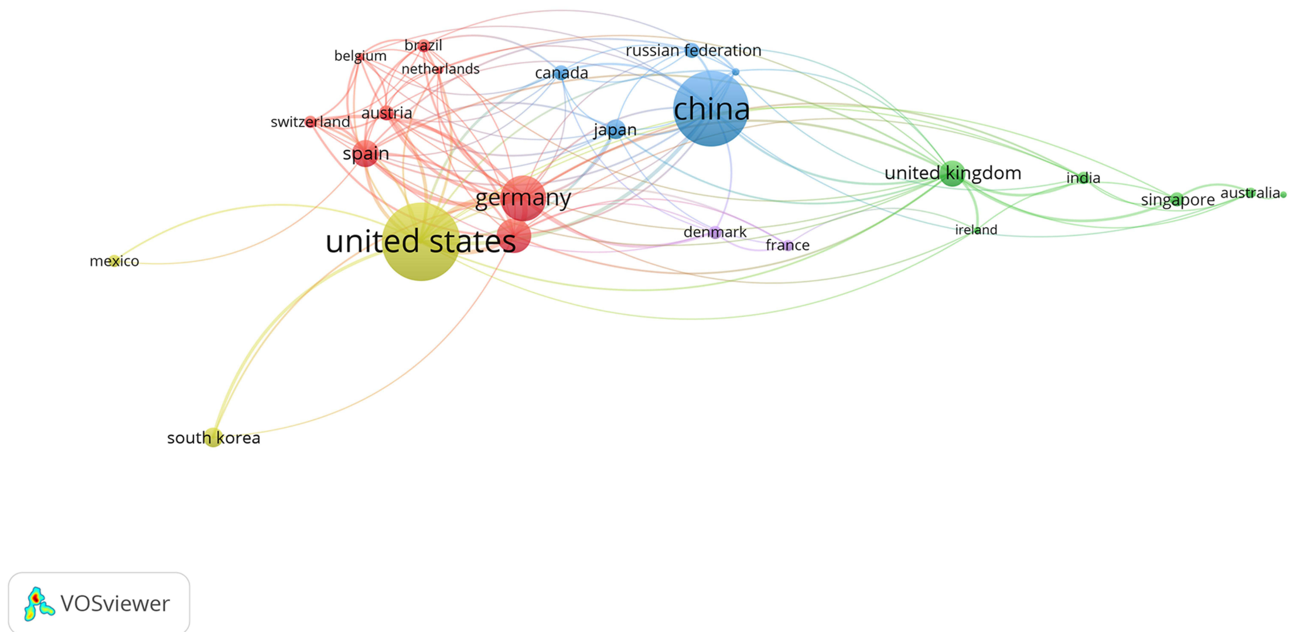

Figure 3 Collaboration network of countries or regions.

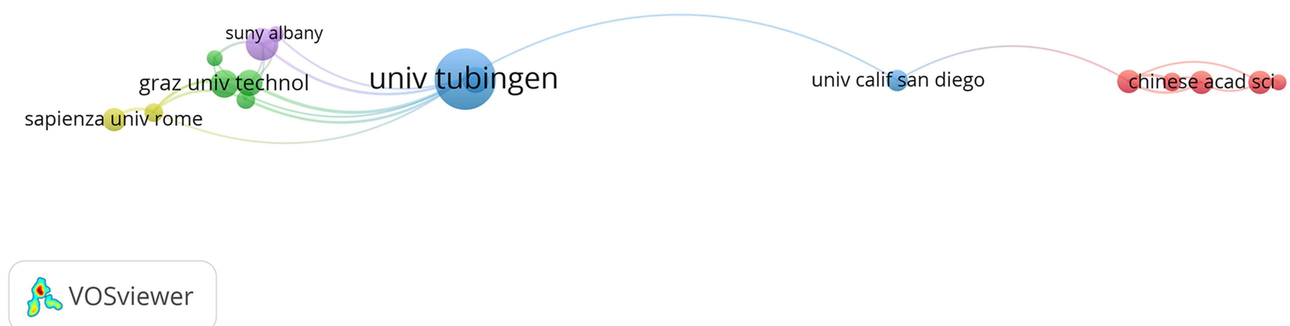

Figure 4 The map of the institution's collaborative network.

Although China ranks second globally in total publications, its research institutions are relatively scattered, with fewer papers per institution. This suggests that there is a need for stronger collaboration among Chinese institutions to enhance their collective output and influence in the field.

Table 2 Top 10 Institutions Ranked by Number of Publications

Institutions	Documents	Citations	Avg. Citations	Avg. Pub. Year	TLS	Country
University of Tubingen	26	5033	43.6009	2013.769	41	Germany
New York state dept hlth	13	5099	19.8201	2008.539	17	USA
Graz University of Technology	11	1544	9.4025	2010	10	Austrian
Keio University	10	591	10.4407	2016.4	4	Japan
University of Wurzburg	10	1140	8.8238	2013.2	20	Germany
Chinese Academy of Sciences	9	164	17.8878	2019.778	10	China
Fudan University	9	145	6.8854	2020.778	10	China
Sapienza University of Rome	9	62	5.0527	2021.333	8	Italy
Tsinghua University	9	786	14.9522	2019	8	China
University of California San Diego	8	543	12.0515	2017.75	5	USA

 https://doi.org/10.2147/JMDH.S509747

Journal Analysis

Academic journals serve as vital platforms for researchers to disseminate their findings, playing a crucial role in reflecting the quality of research. To conduct a comprehensive analysis, we selected journals that published four or more articles, ultimately including 23 qualifying journals in the study.

Among these, Frontiers in Neuroscience stands out as the journal with the highest number of publications related to BCI in rehabilitation, contributing a total of 34 articles. However, the journal with the most citations is IEEE Transactions on Neural Systems and Rehabilitation Engineering (IEEE Trans. Neural Syst. Rehabil. Eng), with its 8 published papers collectively cited 2,542 times, averaging 317.75 citations per article. This journal has the highest average citation count, indicating that its published articles have a significant impact and receive substantial attention from scholars in the field (Table 3).

Of the journals analyzed, 10 have published more than 8 papers, while the rest have fewer than 8 publications. In Figure 5A, node size corresponds to the number of publications, different colors represent clusters, and line width indicates the strength of relationships between journals. The top 10 journals span the first and second regions of the Journal Citation Indicator (JCI) quartiles.

The dual-map overlay analysis shown in Figure 5B provides an overview of the coverage across different academic journals and illustrates the citation pathways across various thematic fields. The labels on the left side of the dual map represent the disciplines covered by the citing journals, while the labels on the right represent the disciplines of the cited journals. Most journals originate from fields such as molecular biology, immunology, medical sciences, clinical medicine, neurology, sports, and ophthalmology, which are considered research frontiers. The cited articles primarily come from journals in fields such as molecular biology, sports, rehabilitation, psychology, education, and social sciences, which form the knowledge base.

The boundaries between citing and cited journals indicate the communication and connections between these fields, with node labels representing the disciplines housed within different journals. The horizontal axis of the ellipses reflects the number of related authors, while the vertical axis indicates the number of journals in which they have published. This dual-map overlay analysis offers insights into the interdisciplinary nature of research on BCI in rehabilitation medicine and highlights the diverse range of disciplines contributing to and influencing this field.

Author Analysis

Figure 6 illustrates authors with at least five publications in the field of brain-computer interfaces (BCI) in rehabilitation medicine. The statistical mapping includes a total of 17 authors, categorized into five clusters represented by consistent colors, as detailed in Table 4. The top 10 scholars in this research domain collectively contributed 93 articles, accounting for 21.83% of the total publications, with a cumulative citation count of 7,555.

Table 3 Top 10 Journals in Terms of the Number of Published Papers

Institutions	Documents	Citations	Avg. Citations	Avg. Pub. Year	Country	IF (2023)	Quartile
Frontiers in Neuroscience	34	1282	193.5769	2019.559	Switzerland	3.2	Q2
IEEE Trans. Neural Syst. Rehabil. Eng.	24	1488	392.2308	2016.125	USA	4.8	Q1
Frontiers in Human Neuroscience	22	910	140.3636	2018.773	Switzerland	2.4	Q2
Journal of Neural Engineering	19	950	59.1	2017.842	United Kingdom	4	Q2
Sensors	14	1559	114	2019.214	Switzerland	3.4	Q2
Journal of Neuroengineering and Rehabilitation	12	649	18.2222	2018	England	5.2	Q1
Archives of Physical Medicine and Rehabilitation	11	557	16.1111	2015.364	USA	4.3	Q1
Frontiers in Neurology	8	42	6.8889	2020.75	Switzerland	2.7	Q2
IEEE Transactions on Biomedical Engineering	8	2542	87.3333	2015.875	USA	4.4	Q2
PLOS ONE	8	327	67.875	2015.875	USA	2.9	Q1

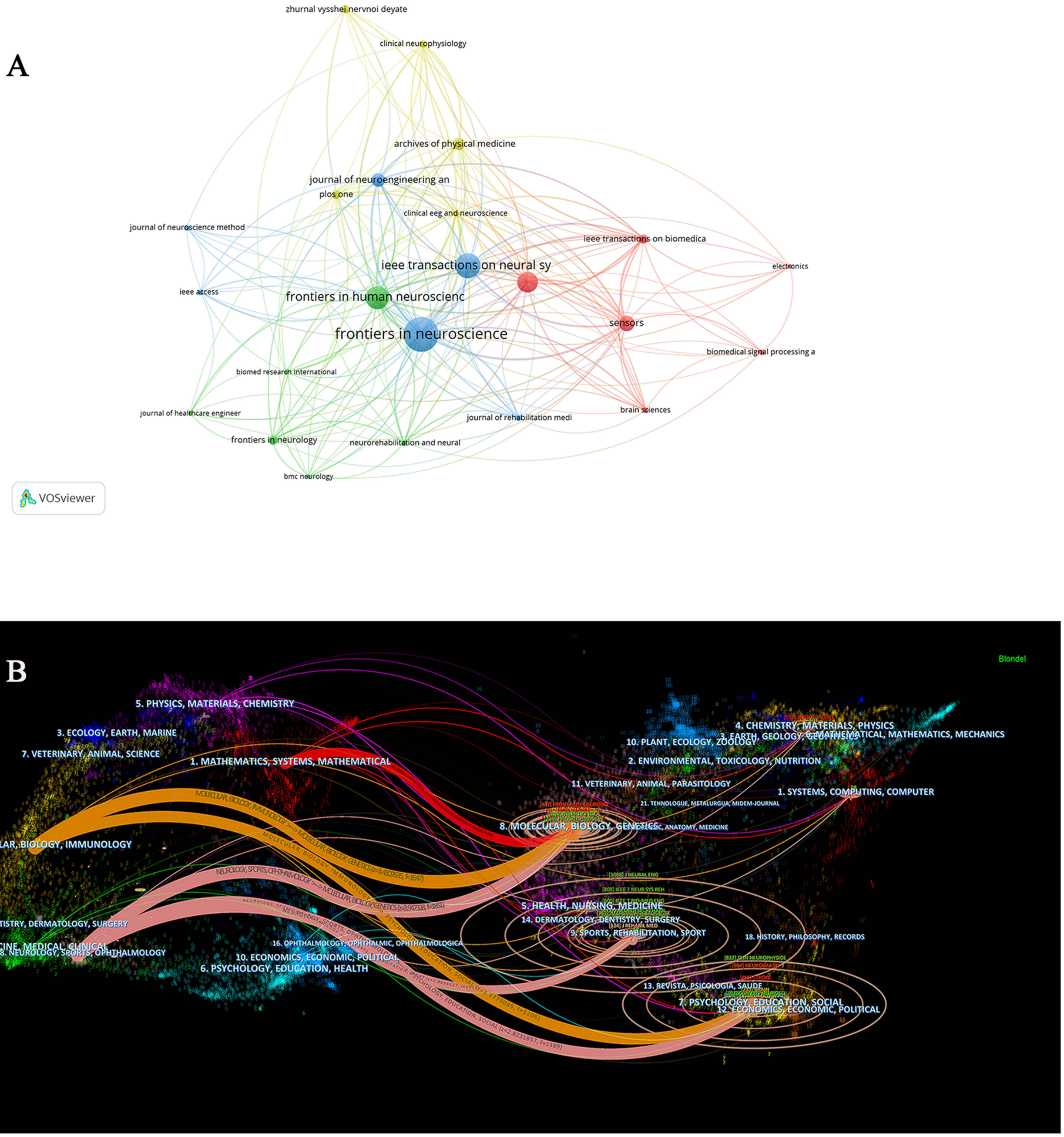

Figure 5 (**A**) Bibliographic coupling analysis of high publication volume journals, visualization maps. (**B**) The dual-map overlay of journals.

Among these authors, Niels Birbaumer, affiliated with the University of Tübingen, Institute of Medical Psychology and Behavioral Neurobiology, is the most prolific contributor, having published 14 relevant articles. His work shows substantial collaboration with other researchers in the field. Birbaumer's publications have garnered 2,198 citations, resulting in an average of 157 citations per article, indicating that he has produced highly influential works in this area and affirming his status as an authority in BCI research.

Notably, Birbaumer's article titled "Brain-computer interfaces for communication and rehabilitation" has been cited 519 times, and the journal in which it was published has an impact factor of 28.2.[30] Additionally, his work "BCI2000: A general-purpose, brain-computer interface (BCI) system" has received 1,806 citations, marking it as a seminal article in the field.[31]

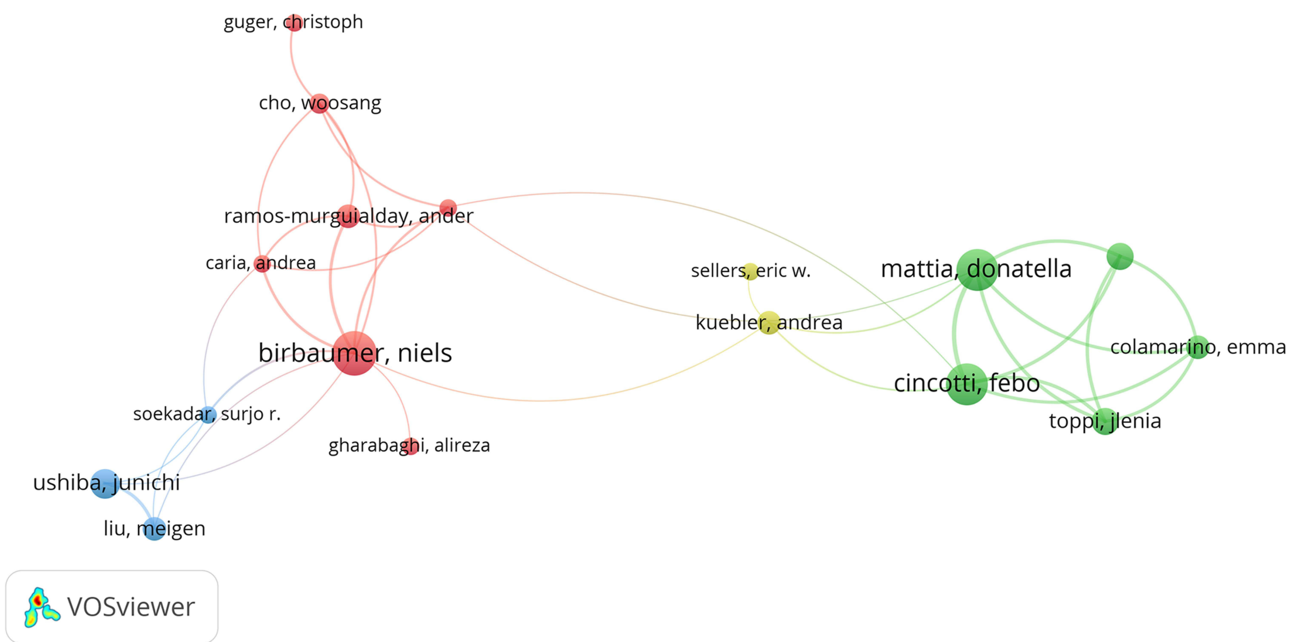

Figure 6 Cooperation map of authors from 2003 to 2024.

Analysis of Keywords and Emerging Trends

The analysis of keyword evolution and frequency changes can help identify the frontiers and emerging themes in research. Keywords with high frequency and centrality values represent hotspots in research over the past two decades, while keywords with high citation bursts indicate future research frontiers.

In Figure 7A, VOSviewer categorizes 80 keywords into four clusters. As of January 31, 2024, the top three high-frequency keywords are "rehabilitation", "brain-computer interface", and "stroke". Figure 7B utilizes CiteSpace and the classic Log-Likelihood Ratio (LLR) algorithm to generate 11 clusters. With Q = 0.4924 and S = 0.7698, values exceeding Q > 0.3 and S > 0.5 indicate significant clustering within the network, suggesting consistency among the literature within each cluster. The largest cluster, #0, centers on "functional connectivity", while other subthemes include "stroke rehabilitation" (#1) and "functional electrical stimulation" (#2).

Figure 8 highlights the top 25 keywords with the strongest citation bursts. The left endpoint of the red line indicates the time of emergence, while the right endpoint marks the end of the burst. Recently emerged keywords underscore

Table 4 Top 10 Authors Ranked by Number of Publications

Author	Country	Institution	Publications	Citations	TLS	H-index
Birbaumer, Niels	Germany	University of Tuebingen	14	2198	25	116
Cincotti, Febo	Italy	Sapienza University Rome	13	762	39	55
Mattia, Donatella	Italy	Sapienza University Rome	13	762	39	52
Ushiba, Junichi	Japan	Keio University	9	555	9	29
Pichiorri, Floriana	Italy	Sapienza University Rome	8	406	31	16
Toppi, Jlenia	Italy	Sapienza University Rome	8	406	31	23
Colamarino, Emma	Italy	Sapienza University Rome	7	34	28	4
Kuebler, Andrea	Germany	University of Wurzburg Eberhard Karls University of Tubingen	7	454	6	67
Liu, Meigen	Japan	Keio University	7	555	25	39
Ramos-Murguialday, Ander	Spain	Athenea Neuroclin TECNALIA Basque Res & Technol Alliance	7	1423	15	38

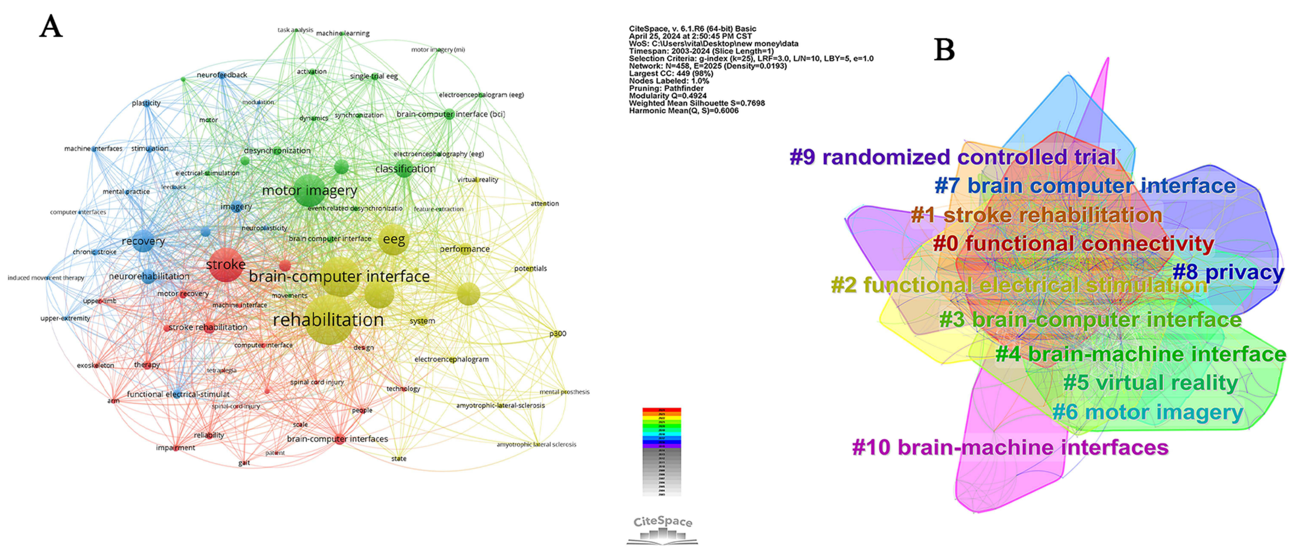

Figure 7 (**A**) Co-occurrence analysis of keywords by overlay visualization. (**B**) Cluster analysis of keywords.

current research hotspots, with "motor recovery", "task analysis", and "functional recovery" identified as focal points and frontiers in future research related to BCI and rehabilitation medicine.

Analysis of References

The co-citation analysis serves as a valuable tool for exploring closely related research topics within an academic field. As shown in Figure 9, a total of 191 articles meet the criterion of having been cited at least 20 times. The citation frequency of an article is a crucial indicator of its academic significance and impact; higher citation counts suggest greater interest and influence within the scholarly community. Table 5 shows the top 10 co-cited references in citations.

Table 5 lists the most cited article published in the IEEE Transactions on Biomedical Engineering, titled "BCI2000: A General-Purpose Brain-Computer Interface (BCI) System". This article, which has been cited 1,806 times since its publication in 2004, has remained relevant for two decades. It offers a comprehensive and in-depth introduction to the BCI2000 system, detailing its architecture, modular components, functions, and communication protocols. This work provides a foundational understanding and theoretical support for subsequent researchers, making it a vital reference for those seeking to comprehend and utilize the BCI2000 system. The primary content of the paper includes: (1) Background Discussion: Numerous laboratories have initiated the development of brain-computer interface (BCI) systems to assist individuals with severe motor impairments. However, further development and practical application necessitate a systematic evaluation and comparison of various brain signals, recording methods, and processing algorithms. Existing BCI systems are unsuitable for this type of research, leading to the introduction of the BCI2000 system.(2) System Architecture Overview: The BCI2000 system comprises four key modules: the operator module, signal source module, signal processing module, and application module. The operator module serves as the central hub for system configuration and result display; the signal source module is responsible for acquiring EEG signals; the signal processing module performs preprocessing, feature extraction, and pattern recognition; the application module translates processed signals into control commands for external devices.(3) Information Transmission: During system operation, information can flow from the signal source module to the signal processing module and then to the application module, with the potential for feedback to the signal source module, thus forming a complete information transmission loop.(4) Experimental Validation: The authors utilized the BCI2000 system to develop various BCI systems, conducting experiments across different brain signals, processing methods, and application scenarios. The results indicated that these systems performed well in online operations, meeting the stringent real-time requirements of BCI applications. (5) Application Case Studies: The paper presents several application instances of the BCI2000 system, including cursor control through sensorimotor rhythm modulation, simple spelling applications based on sensorimotor rhythms, cursor

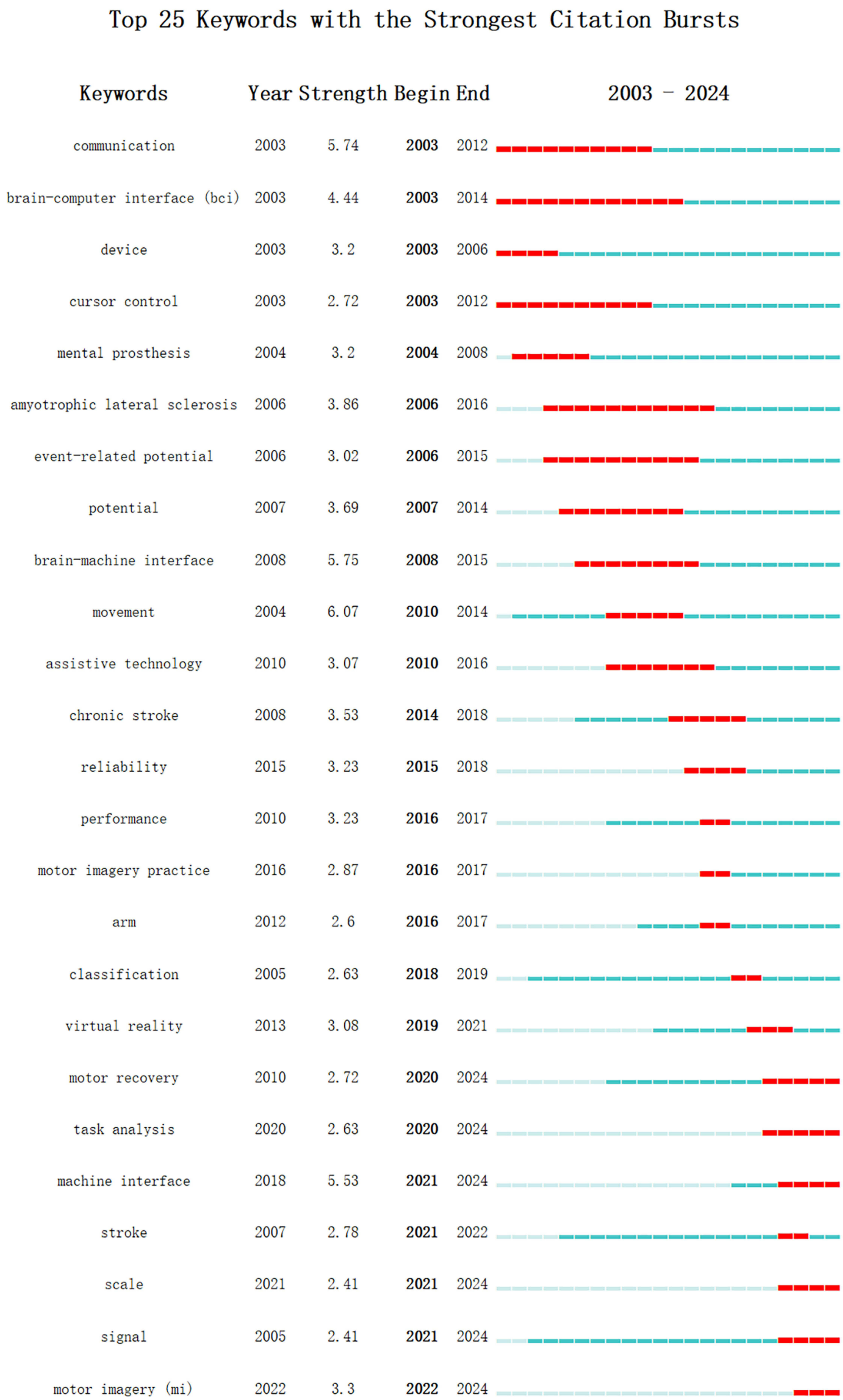

Figure 8 Top 25 keywords with the strongest citation bursts.

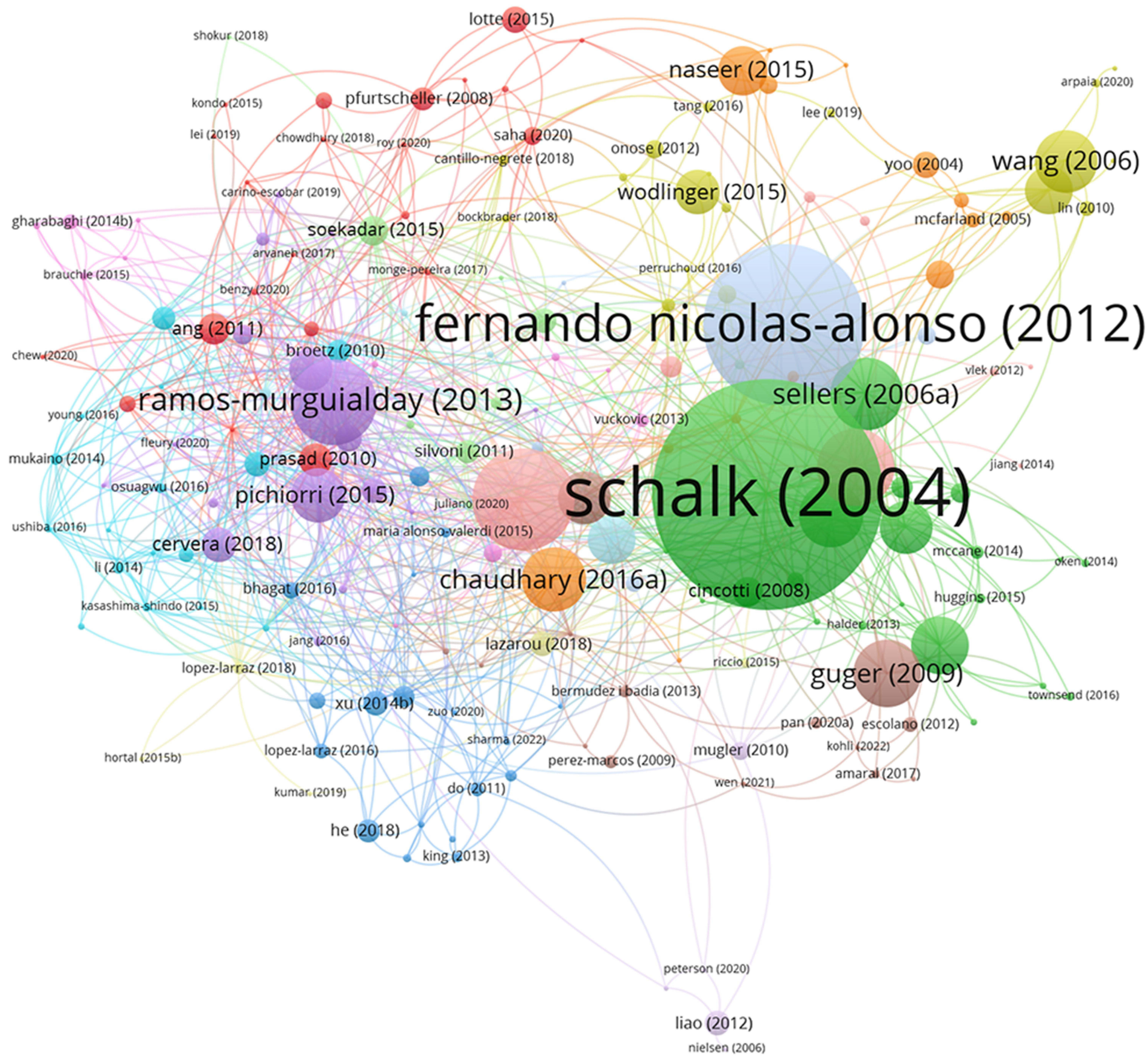

Figure 9 Network diagram of co-cited references.

control via slow cortical potentials, and spelling applications based on the P300 potential. This thorough exploration of the BCI2000 system illustrates its significance and enduring influence on the field of brain-computer interfaces and rehabilitation medicine.

Discussion

Bibliometrics is a systematic tool for in-depth exploration of academic literature and research findings within related fields.[32] Despite numerous clinical trials conducted on the applications of brain-computer interfaces (BCI) in rehabilitation medicine,[12,33–35] there remains a significant gap in bibliometric studies specifically addressing this topic. Through the quantitative analysis of extensive literature, bibliometrics can effectively illustrate research hotspots, frontier directions, and developmental trends within a specific academic domain, thereby providing critical insights for researchers in selecting their study topics. Furthermore, bibliometric analysis evaluates the impact of scientific achievements based on metrics such as citation counts and download frequencies, offering an objective assessment of the influence of research outputs, scholars, and institutions. This process facilitates academic communication and collaboration while

Table 5 Top 10 Co-Cited References in Citations

Title	First Author	Citations	Journal	IF (2022)	Pub. Year	Quartile
BCI2000: A General-Purpose Brain-Computer Interface (BCI) System	Birbaumer, Niels	1806	IEEE Trans. Neural Syst. Rehabil. Eng.	4.8	2004	Q2
Brain Computer Interfaces, a Review	Nicolas-Alonso	1225	*Sensors*	3.4	2012	Q1
Brain–computer interfaces in neurological rehabilitation	Daly Janis J	731	The Lancet Neurology	46.5	2008	Q1
Brain–machine interface in chronic stroke rehabilitation: A controlled study	Ramos-Murguialday Ander	607	Annals of Neurology	8.1	2013	Q1
Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges	Millán José Del R.	549	Front. Neurosci	3.2	2010	Q2
A P300-based brain–computer interface: Initial tests by ALS patients	Sellers Eric W.	508	Clinical Neurophysiology	3.7	2006	Q1
How many people are able to control a P300-based brain–computer interface (BCI)?	Guger Christoph	468	Neurosci Lett	2.5	2009	Q3
A P300-based brain–computer interface for people with amyotrophic lateral sclerosis	Nijboer F.	446	Clinical Neurophysiology	3.7	2008	Q1
Brain–computer interfaces for communication and rehabilitation	Chaudhary Ujwa	444	Nat Rev Neurol	28.2	2016	Q1
A practical VEP-based brain-computer interface	Yijun Wang	426	IEEE Trans. Neural Syst. Rehabil. Eng.	4.8	2006	Q1

promoting the dissemination and innovation of knowledge. By uncovering the patterns and bottlenecks in knowledge transfer, bibliometric analysis fosters the rapid propagation and innovative development of scientific knowledge across various fields and regions.

General Information

This study represents the first global bibliometric analysis of the application of BCI in rehabilitation medicine. Utilizing bibliometric analysis tools such as VOSviewer and CiteSpace, we examined 426 articles from the Web of Science Core Collection (WoSCC) database, aiming to delineate research hotspots and forecast future trends over the past 20 years. Since 2003, the trajectory of publications has exhibited a sustained upward trend, peaking in 2021. The publication trend graph reveals a peak in publication volume between 2019 and 2021. Several factors contributed to this surge. From a technological advancement perspective, breakthroughs in key areas of brain-computer interface (BCI) technology occurred around 2019. Innovations such as novel electrode materials significantly improved signal acquisition accuracy, while optimized algorithms enabled more precise signal processing and interpretation. These advancements expanded the scope of research, encouraging scientists to explore new application scenarios, which led to a surge in published studies.[36,37] In terms of funding, governments and research institutions worldwide increasingly recognized the immense potential of BCI technology in fields such as healthcare and defense. This realization resulted in increased funding, further fueling research and development in the field. From a clinical application standpoint, the period from 2019 to 2021 saw notable progress in the use of BCIs in rehabilitation therapies and the diagnosis and treatment of neurological disorders. These emerging clinical applications highlighted the practical value of BCIs, driving greater interest among researchers.[38,39] The close interaction between clinical needs and research outcomes generated a wealth of new research topics and findings, which were reflected in the growth of publication volume during this time.

Based on the current publishing patterns, our analysis anticipates a continuous and steady increase in the volume of publications in the foreseeable future. In the field of BCI in rehabilitation medicine, the United States has been the leading country in terms of publication output over the past 20 years, contributing 102 articles. China follows as the leading developing country with a total of 98 publications. The University of Tuebingen stands out as the most prolific research institution, with 26 articles published, while the New York State Department of Health ranks second, with 13 articles. Among authors, Niels Birbaumer has published the highest number of articles in this field, totaling 14, with the most citations at 2,198. His extensive collaboration with other scholars indicates his significant influence within this domain. Based on the current classification of themes related to BCI and rehabilitation medicine, the primary disciplines involved include neurosciences, biomedical engineering, rehabilitation, and clinical neurology.

The United States, China, and Germany lead brain-computer interface (BCI) research, driven by distinct factors. The US government, particularly Defense Advanced Research Projects Agency (DARPA), heavily funds BCI projects, attracting top researchers and accelerating advancements. China's rapid progress stems from strong national support, initiatives like the "Science and Technology Innovation 2030—Major Projects", and robust academia-industry collaboration, leading to increased publications and patents.[40] Germany leverages its industrial strength and interdisciplinary research, integrating neuroscience, engineering, and computer science to drive innovation. Beyond these leaders, countries like Japan, Italy, the UK, and Australia contribute to foundational BCI research, though their impact is less reflected in publication metrics. Some developing nations have made notable strides in specific applications—India focuses on BCI in education, enhancing learning through attention-monitoring devices, while Brazil explores BCI in neurological rehabilitation, aiding stroke recovery.[41,42] To amplify global progress, international collaboration should be strengthened through technical and financial support, academic exchanges, and dedicated research funds, fostering coordinated BCI development worldwide.

Analyzing co-cited articles serves a clear purpose and holds significant importance. The primary aim is to examine the phenomenon of multiple studies citing the same article, thereby uncovering the core knowledge and key research points within a specific field. From a functional perspective, co-cited articles play a pivotal role in identifying research hotspots. For example, the article "*Brain-Computer Interfaces, a Review*" provides a comprehensive overview of the fundamental principles, technical architecture, and early application cases of BCIs, establishing a solid theoretical foundation for subsequent studies.[43] Many follow-up works exploring novel BCI algorithms and hardware designs have built upon this framework, driving further expansion and innovation in the field. Similarly, the article *"Brain–Computer Interfaces in Neurological Rehabilitation"* focuses on the application of BCIs in neurological rehabilitation.[44] It offers an in-depth discussion on technical considerations during the application process and outlines methods for evaluating clinical outcomes. These foundational works have significantly contributed to advancing research and guiding practical implementations in their respective areas.

Research Hotspots and Frontiers

From the bibliometric analysis, we can conclude that the current research hotspots concerning the application of BCI in rehabilitation medicine include the following key areas: motor imagery, motor recovery, and task analysis.

Motor Imagery

Motor imagery refers to the internal simulation of specific movements in the brain without any actual motor output. In the field of brain-computer interfaces (BCI), when patients engage in motor imagery, specific regions of the brain generate neural activity patterns similar to those associated with actual movements.[45] BCI devices can detect these neural activity signals and convert them into commands that control external devices.[46]

The application of motor imagery in rehabilitation medicine offers numerous advantages. It facilitates neural plasticity by activating brain regions associated with movement, thereby promoting the development of neural connections. For patients experiencing motor impairments due to conditions such as stroke or spinal cord injury, repeated motor imagery training can help re-establish connections in damaged neural pathways, ultimately aiding in the recovery of motor function.[47] Research indicates that combining motor imagery with actual motor training can significantly enhance rehabilitation outcomes.[48] Personalized training programs can be designed based on the specific needs of patients. For instance, in patients with upper limb paralysis, targeted upper limb motor imagery tasks can be developed to specifically train the relevant neural pathways. BCI devices can monitor patients' neural activity in real time, adjusting the difficulty and intensity of training to ensure its effectiveness and safety.[49]

Moreover, integrating motor imagery with BCI enhances patient engagement and motivation. Traditional rehabilitation methods can often be monotonous, leading to a loss of interest among patients. In contrast, motor imagery training allows patients to perform a variety of engaging movement tasks in a virtual environment, thus increasing their participation and enthusiasm.[50] Through BCI devices, patients can directly visualize their neural activity signals and training outcomes, boosting their confidence and motivation in the rehabilitation process.

Currently, many technical innovations are emerging in the integration of motor imagery with BCI. With the continuous advancement of BCI technology, the accuracy and stability of motor imagery detection have significantly improved. Novel electroencephalography (EEG) signal acquisition devices and algorithms can better capture neural activity signals related to motor imagery while minimizing interference and noise.[51,52]

An increasing number of clinical studies indicate that the combination of motor imagery and brain-computer interface (BCI) technology demonstrates significant therapeutic efficacy in the rehabilitation of conditions such as stroke, spinal cord injury, and Parkinson's disease. Researchers are actively exploring various training modalities and parameters to optimize rehabilitation protocols.[53,54] Long-term follow-up studies are also underway to evaluate the enduring effects and sustainability of motor imagery training.

The future development of motor imagery combined with BCI can be directed toward several key areas: (1) Multimodal Brain-Computer Interfaces: The integration of various neural signal detection technologies, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and near-infrared spectroscopy (NIRS), can enhance the accuracy and reliability of motor imagery detection. By consolidating information from different modalities, a more comprehensive understanding of the brain's activity can be achieved, providing more precise guidance for rehabilitation interventions.(2) Intelligent Rehabilitation Systems: The development of intelligent motor imagery rehabilitation systems that can automatically adjust training protocols based on patients' real-time neural activity signals and rehabilitation progress is essential. Utilizing artificial intelligence to analyze and mine large volumes of clinical data can offer personalized rehabilitation recommendations and predictions for recovery outcomes.[55] (3) Home Rehabilitation Applications: With the miniaturization and portability of BCI technology, there is potential to expand motor imagery rehabilitation training into home environments. Patients will be able to engage in self-directed training at home, thereby enhancing the convenience and adherence to rehabilitation protocols. The advancement of telemedicine will further support home rehabilitation by allowing healthcare providers to remotely monitor patients' training progress and offer guidance.[56,57]

In the realm of home rehabilitation, the application of home-based brain-computer interface (BCI) systems has significantly enhanced the accessibility of rehabilitation services for patients. With such systems, patients can conduct rehabilitation training at home, saving both time and effort. Additionally, the familiar home environment facilitates the collection of stable electroencephalographic (EEG) signals, thereby improving the effectiveness of rehabilitation. Family members can also actively participate in the process, fostering greater patient engagement and further enhancing rehabilitation outcomes. Despite these advancements, multimodal BCI systems face numerous technical challenges. During signal acquisition, the accuracy and stability of EEG, electromyographic (EMG), and eye movement signals are often affected by environmental factors and individual differences, highlighting an urgent need for improvement.[58,59] Signal integration is another major hurdle—efficiently fusing multimodal signals and extracting accurate and representative features to achieve precise human-computer interaction remains a core research focus and a significant challenge. Furthermore, the real-time performance and portability of these systems are critical obstacles; meeting these requirements is essential for enabling practical and widespread applications.[60]

In conclusion, motor imagery is a focal point in the integration of BCI technology within rehabilitation medicine, exhibiting substantial application potential and developmental prospects. Through continuous technological innovations and clinical research, the combination of motor imagery and BCI technology holds the promise of providing new hope for patients with motor function impairments.

Motor Recovery

Motor recovery has emerged as a prominent research focus in the application of brain-computer interfaces (BCI) within rehabilitation medicine, driven primarily by clinical needs. Many patients suffer from impaired motor function due to conditions such as stroke, spinal cord injury, and traumatic brain injury, significantly impacting their quality of life.[61] Traditional rehabilitation methods often yield limited results and involve lengthy recovery processes. In contrast, BCI technology offers new hope for these patients by enabling direct interaction with the brain, bypassing damaged neural pathways, stimulating brain plasticity, and promoting the restoration of motor function.

Currently, the technical feasibility of BCI is relatively advanced, benefiting first from progress in signal acquisition and processing technologies. Modern BCI systems can accurately capture and analyze brain signals, such as electroencephalography (EEG) and functional magnetic resonance imaging (fMRI).[62] These technologies facilitate real-time monitoring of brain activity, providing precise feedback for motor recovery. Additionally, the application of machine learning and artificial intelligence algorithms enables efficient decoding and classification of brain signals, allowing for the identification of patients' motor intentions and the control of external devices, such as prosthetics and exoskeletons, to assist patients in motor training.[63]

A substantial body of research indicates that BCI yield significant clinical effects in functional recovery. The combination of BCI technology with rehabilitation training can markedly enhance the speed and extent of motor function recovery. For instance, rehabilitation robots controlled by BCI can deliver personalized training programs, adjusting intensity and difficulty based on the patient's individual circumstances, thereby improving training outcomes.

The interdisciplinary nature of BCI technology provides a unique advantage, as its application in rehabilitation medicine encompasses various fields, including neuroscience, engineering, and rehabilitation medicine. This multidisciplinary integration allows researchers to explore more effective rehabilitation methods from different perspectives.[64] For example, neuroscientists can investigate the mechanisms of brain plasticity, engineers can develop more advanced BCI devices, and rehabilitation specialists can formulate personalized rehabilitation strategies.

In summary, the focus on motor recovery as a key research area in the application of BCI within rehabilitation medicine results from a confluence of factors, including clinical demands, advancements in technical feasibility, significant rehabilitation outcomes, and the benefits of interdisciplinary collaboration. As technology continues to progress, the prospects for BCI applications in rehabilitation medicine are expected to expand even further.

Signals

Within the realm of brain-computer interface (BCI) applications in rehabilitation medicine, signals have emerged as a significant research focus for several reasons: (1) Technical Feasibility: BCI rely heavily on the accurate acquisition and interpretation of brain signals. Advances in sensor technology and signal processing algorithms have enabled more precise capture of various brain signals, such as electroencephalography (EEG), functional magnetic resonance imaging (fMRI), and functional near-infrared spectroscopy (fNIRS).[65–67] These signals provide the technical foundation for the application of BCI in rehabilitation medicine.(2) Rehabilitation Needs: For patients with motor function impairments, BCI can decode signals related to brain movement intentions and convert them into control commands for external devices, helping patients actively engage in rehabilitation training. For instance, patients paralyzed due to conditions like stroke or spinal cord injury can use BCI to control robotic arms via brain signals, enhancing their ability to perform daily activities. In the case of cognitive impairments, monitoring cognitive signals—such as attention and memory-related EEG signals—can help assess a patient's cognitive state and facilitate the design of targeted rehabilitation programs.[12] For example, BCI can monitor brain activity in patients with cognitive disorders like Alzheimer's disease, allowing for timely adjustments to rehabilitation training intensity and content.(3) Research Advances: Recent years have seen significant breakthroughs in BCI signal processing research. Researchers have developed more efficient signal decoding algorithms capable of extracting valuable information from complex brain signals. Moreover, the evolution of multimodal signal fusion techniques integrates various types of brain signals, enhancing both accuracy and reliability. These advancements have further fueled enthusiasm for research in BCI signals.[68] (4) Future Development Potential: The research on BCI signals holds not only broad application prospects in rehabilitation medicine but also the potential for significant impacts in other fields. For instance, long-term monitoring of brain signals can facilitate early diagnosis and prevention of neurological disorders. Furthermore, the integration of BCI signals with artificial intelligence technology promises the development of more intelligent rehabilitation devices and treatment methods.[69,70] (5) In the transition of brain-computer interface (BCI) technology toward clinical applications, advancements in signal processing are crucial for enhancing its clinical utility. In rehabilitation settings, patients rely on BCI devices for motor assistance and training. Accurate signal classification enables the system to promptly interpret patient intent, minimizing erroneous actions and ensuring safe and efficient device operation. Furthermore, improvements in real-time signal processing have significantly advanced BCI-based rehabilitation.[71] High-speed hardware and software systems allow for the real-time acquisition, processing, and analysis of electroencephalographic (EEG) signals.[72] During motor imagery training, these advancements enable immediate activation of external devices, thereby enhancing the rehabilitation experience and improving therapeutic outcomes.

In summary, signals have become a research hotspot in the application of BCI within rehabilitation medicine due to their critical significance across multiple dimensions, including technical feasibility, rehabilitation needs, research advancements, and future development potential.

Disorders and Challenges

At the current stage, BCI technology faces several challenges in rehabilitation applications. The high costs associated with system development, production, and maintenance pose significant barriers. High-resolution, high signal-to-noise ratio (SNR) hardware is expensive, and software development requires substantial investment, making BCI-based rehabilitation inaccessible to many patients, particularly in regions with limited healthcare resources.[73] Additionally, ethical concerns regarding brain data privacy and patient autonomy remain critical issues. Electroencephalographic (EEG) data contain sensitive information, and any leakage or misuse could compromise patient rights.[74] Moreover, patients often lack the necessary expertise to make informed decisions about their treatment plans, potentially affecting the scientific validity of their choices. From a technical perspective, signal noise interference remains a major obstacle. Brain signals are inherently weak and complex, making them highly susceptible to various external and physiological factors.[75]

Interdisciplinary collaboration is critical in brain-computer interface (BCI) research. To enhance collaboration efficiency, the following strategies can be implemented.(1) Establish a Regular Communication Mechanism:Regularly organize interdisciplinary seminars involving engineers, clinicians, and neuroscientists to share the latest research findings and clinical practices, fostering knowledge exchange and idea generation. For instance, quarterly BCI frontier technology symposiums can be held with rotating themes such as hardware innovation, clinical case studies, and new discoveries in neuroscience.(2) Initiate Joint Research Projects:For interdisciplinary research teams focused on addressing key challenges in BCI development. For example, in tackling signal noise interference, engineers can improve the anti-interference capabilities of hardware devices, neuroscientists can explore the neurophysiological mechanisms of noise generation, and clinicians can provide clinical data and validate improvements. This collaborative approach ensures that technical problems are addressed comprehensively. (3) Talent Development and Exchange:Encourage cross-disciplinary learning and training among professionals from different fields. Universities and research institutions can offer interdisciplinary courses to cultivate versatile talent skilled in neuroscience principles, engineering technologies, and clinical knowledge. Additionally, support exchange programs where engineers gain firsthand insights into clinical needs, and clinicians and neuroscientists participate in technical development within engineering labs. These strategies promote effective interdisciplinary collaboration, accelerating innovation and advancing the development and application of BCI technology.

Limitations

It is important to acknowledge some limitations of this study. First, we selected data only from the Web of Science (WOS) and did not include literature from other databases. Second, due to language and time constraints, non-English papers and literature published outside the specified period were excluded. Additionally, due to software limitations, modifications to case and abbreviation formats were not possible, and the settings for thresholds and trimming methods may have resulted in some data being cut off.

Conclusion

This bibliometric analysis highlights the field's sustained growth, with increasing scholarly contributions establishing a strong research foundation. Core themes, including motor imagery, motor recovery, and signal processing, remain central, though some areas require further exploration. Collaborative networks among institutions and authors drive knowledge dissemination, yet interdisciplinary engagement remains limited.

To advance the field, future research should address thematic imbalances, foster interdisciplinary collaboration, and integrate emerging technologies to tackle complex challenges. Strengthening these aspects will ensure continued progress and broader real-world impact.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

Disclosure

The authors report no conflicts of interest in this work.

References

1. Vidal JJ. Toward direct brain-computer communication. *Ann Rev Biophys Bioeng*. 1973;2(1):157–180. doi:10.1146/annurev.bb.02.060173.001105
2. Mawase F, Uehara S, Bastian AJ, Celnik P. Motor learning enhances use-dependent plasticity. *J Neurosci*. 2017;37(10):2673–2685. doi:10.1523/JNEUROSCI.3303-16.2017
3. Karikari E, Koshechkin KA. Review on brain-computer interface technologies in healthcare. *Biophys Rev*. 2023;15(5):1351–1358. doi:10.1007/s12551-023-01138-6
4. Kotchetkov IS, Hwang BY, Appelboom G, Kellner CP, Connolly JES. Brain-computer interfaces: military, neurosurgical, and ethical perspective. *Neurosurg Focus*. 2010;28(5):E25. doi:10.3171/2010.2.FOCUS1027
5. Zhang W, Qin Y, Tao X. Decoding brain-controlled intention for UAVs and IVs based on lightweight network. *IEEE Internet Things J*. 2024;11(12):21112–21124. doi:10.1109/JIOT.2024.3367690
6. Orban M, Elsamanty M, Guo K, Zhang S, Yang H. A review of brain activity and eeg-based brain-computer interfaces for rehabilitation application. *Bioengineering*. 2022;9(12):768. doi:10.3390/bioengineering9120768
7. Cervera MA, Soekadar SR, Ushiba J, et al. Brain-computer interfaces for post-stroke motor rehabilitation: a meta-analysis. *Ann Clin Transl Neurol*. 2018;5(5):651–663. doi:10.1002/acn3.544
8. Gao Z, Pang Z, Chen Y, et al. Restoring after central nervous system injuries: neural mechanisms and translational applications of motor recovery. *Neurosci Bull*. 2022;38(12):1569–1587. doi:10.1007/s12264-022-00959-x
9. Wang A, Tian X, Jiang D, et al. Rehabilitation with brain-computer interface and upper limb motor function in ischemic stroke: a randomized controlled trial. *Med*. 2024;5(6):559–569. doi:10.1016/j.medj.2024.02.014
10. Rabhi Y, Mrabet M, Fnaiech F. A facial expression controlled wheelchair for people with disabilities. *Comput Methods Programs Biomed*. 2018;165:89–105. doi:10.1016/j.cmpb.2018.08.013
11. Bockbrader M. Upper limb sensorimotor restoration through brain–computer interface technology in tetraparesis. *Curr Opin Biomed Eng*. 2019;11:85–101. doi:10.1016/j.cobme.2019.09.002
12. Sun X, Li M, Li Q, et al. Poststroke cognitive impairment research progress on application of brain-computer interface. *Biomed Res Int*. 2022;2022:9935116–9935192. doi:10.1155/2022/9935192
13. Lazcano-Herrera AG, Fuentes-Aguilar RQ, Chairez I, Alonso-Valerdi LM, Gonzalez-Mendoza M, Alfaro-Ponce M. Review on bci virtual rehabilitation and remote technology based on eeg for assistive devices. *Appl Sci*. 2022;12(23):12253. doi:10.3390/app122312253
14. Zhang J, Li J, Huang Z, Huang D, Yu H, Li Z. Recent progress in wearable brain-computer interface (bci) devices based on electroencephalogram (eeg) for medical applications: a review. *Health Data Science*. 2023;3:96. doi:10.34133/hds.0096
15. Sakhavi S, Guan C, Yan S. Learning temporal information for brain-computer interface using convolutional neural networks. *IEEE Trans Neural Netw Learn Syst*. 2018;29(11):5619–5629. doi:10.1109/TNNLS.2018.2789927
16. Mccrimmon CM, Fu JL, Wang M, et al. Performance assessment of a custom, portable, and low-cost brain–computer interface platform. *IEEE Trans Biomed Eng*. 2017;64(10):2313–2320. doi:10.1109/TBME.2017.2667579
17. Xu H, Hsu S, Nakanishi M, Lin Y, Jung T, Cauwenberghs G. Stimulus design for visual evoked potential based brain-computer interfaces. *IEEE Trans Neural Syst Rehabil Eng*. 2023;31:1. doi:10.1109/TNSRE.2023.3280081
18. Azab AM, Mihaylova L, Ang KK, Arvaneh M. Weighted transfer learning for improving motor imagery-based brain-computer interface. *IEEE Trans Neural Syst Rehabil Eng*. 2019;27(7):1352–1359. doi:10.1109/TNSRE.2019.2923315
19. Wexler A, Feinsinger A. Ethical challenges in translating brain–computer interfaces. *Nat Hum Behav*. 2024;8(10):1831–1833. doi:10.1038/s41562-024-01972-y
20. Maynard AD, Scragg M. The ethical and responsible development and application of advanced brain machine interfaces. *J Med Internet Res*. 2019;21(10):e16321. doi:10.2196/16321
21. Saha S, Mamun KA, Ahmed K, et al. Progress in brain computer interface: challenges and opportunities. *Front Syst Neurosci*. 2021;15:578875. doi:10.3389/fnsys.2021.578875
22. Safavi F, Olikkal P, Pei D, et al. Emerging frontiers in human–robot interaction. *J Intell Robot Syst*. 2024;110(2):45. doi:10.1007/s10846-024-02074-7

23. Waqas A, Teoh SH, Lapão LV, Messina LA, Correia JC. Harnessing telemedicine for the provision of health care: bibliometric and scientometric analysis. *J Med Internet Res*. 2020;22(10):e18835. doi:10.2196/18835
24. Zhang J, Song L, Jia J, et al. Knowledge mapping of necroptosis from 2012 to 2021: a bibliometric analysis. *Front Immunol*. 2022;13:917155. doi:10.3389/fimmu.2022.917155
25. Deng P, Wang S, Sun X, et al. Global trends in research of gouty arthritis over past decade: a bibliometric analysis. *Front Immunol*. 2022;13:910400. doi:10.3389/fimmu.2022.910400
26. Chen H, Fang T, Liu F, et al. Career adaptability research: a literature review with scientific knowledge mapping in web of science. *Int J Environ Res Public Health*. 2020;17(16). doi:10.3390/ijerph17165986
27. Arruda H, Silva ER, Lessa M, Proenca DJ, Bartholo R. Vosviewer. *J Med Libr Assoc*. 2022;110(3):392. doi:10.5195/jmla.2022.1434
28. Chen C. Citespace ii: detecting and visualizing emerging trends and transient patterns in scientific literature. *J Am Soc Inf Sci Technol*. 2006;57(3):359–377. doi:10.1002/asi.20317
29. Chen C, Hu Z, Liu S, Tseng H. Emerging trends in regenerative medicine: a scientometric analysis in citespace. *Expert Opin Biol Ther*. 2012;12(5):593–608. doi:10.1517/14712598.2012.674507
30. Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. *Nat Rev Neurol*. 2016;12(9):513–525. doi:10.1038/nrneurol.2016.113
31. Schalk G, Mcfarland DJ, Hinterberger T, Birbaumer N, Wolpaw JR. Bci2000: a general-purpose brain-computer interface (bci) system. *IEEE Trans Biomed Eng*. 2004;51(6):1034–1043. doi:10.1109/TBME.2004.827072
32. Li X, Zhang J, Zhang S, et al. Biomarkers for neuromyelitis optica: a visual analysis of emerging research trends. *Neural Regen Res*. 2024;19(12):2735–2749. doi:10.4103/NRR.NRR-D-24-00109
33. Cheng N, Phua KS, Lai HS, et al. Brain-computer interface-based soft robotic glove rehabilitation for stroke. *IEEE Trans Biomed Eng*. 2020;67(12):3339–3351. doi:10.1109/TBME.2020.2984003
34. Daly JJ, Wolpaw JR. Brain-computer interfaces in neurological rehabilitation. *Lancet Neurol*. 2008;7(11):1032–1043. doi:10.1016/S1474-4422(08)70223-0
35. Tayebi H, Azadnajafabad S, Maroufi SF, et al. Applications of brain-computer interfaces in neurodegenerative diseases. *Neurosurg Rev*. 2023;46(1):131. doi:10.1007/s10143-023-02038-9
36. Abiri R, Borhani S, Sellers EW, Jiang Y, Zhao X. A comprehensive review of eeg-based brain-computer interface paradigms. *J Neural Eng*. 2019;16(1):11001. doi:10.1088/1741-2552/aaf12e
37. De Vico Fallani F, Bassett DS. Network neuroscience for optimizing brain-computer interfaces. *Phys Life Rev*. 2019;31:304–309. doi:10.1016/j.plrev.2018.10.001
38. Wood H. Bidirectional brain–computer interface aids robotic arm control. *Nat Rev Neurol*. 2021;17(8):462. doi:10.1038/s41582-021-00527-3
39. Rossi F, Savi F, Prestia A, Mongardi A, Demarchi D, Buccino G. Combining action observation treatment with a brain-computer interface system: perspectives on neurorehabilitation. *Sensors*. 2021;21(24):8504. doi:10.3390/s21248504
40. Liu Y, Zhao Z, Xu M, et al. Decoding and synthesizing tonal language speech from brain activity. *Sci Adv*. 2023;9(23):eadh478. doi:10.1126/sciadv.adh0478
41. Gupta A, Agrawal RK, Kirar JS, et al. A hierarchical meta-model for multi-class mental task based brain-computer interfaces. *Neurocomputing*. 2020;389:207–217. doi:10.1016/j.neucom.2018.07.094
42. Zanona ADF, Piscitelli D, Seixas VM, et al. Brain-computer interface combined with mental practice and occupational therapy enhances upper limb motor recovery, activities of daily living, and participation in subacute stroke. *Front Neurol*. 2023;13:1041978. doi:10.3389/fneur.2022.1041978
43. Nicolas-Alonso LF, Gomez-Gil J. Brain computer interfaces, a review. *Sensors*. 2012;12(2):1211–1279. doi:10.3390/s120201211
44. Daly JJP, Wolpaw JRM. Brain–computer interfaces in neurological rehabilitation. *Lancet Neurol*. 2008;7(11):1032–1043. doi:10.1016/S1474-4422(08)70223-0
45. Cho H, Ahn M, Ahn S, Kwon M, Jun SC. Eeg datasets for motor imagery brain–computer interface. *Gigascience*. 2017;6(7):1–8. doi:10.1093/gigascience/gix034
46. Lin BS, Pan JS, Chu TY, Lin BS. Development of a wearable motor-imagery-based brain-computer interface. *J Med Syst*. 2016;40(3):71. doi:10.1007/s10916-015-0429-6
47. Lu RR, Zheng MX, Li J, et al. Motor imagery based brain-computer interface control of continuous passive motion for wrist extension recovery in chronic stroke patients. *Neurosci Lett*. 2020;718:134727. doi:10.1016/j.neulet.2019.134727
48. Park S, Ha J, Kim L. Improving performance of motor imagery-based brain-computer interface in poorly performing subjects using a hybrid-imagery method utilizing combined motor and somatosensory activity. *IEEE Trans Neural Syst Rehabil Eng*. 2023;31:1064–1074. doi:10.1109/TNSRE.2023.3237583
49. Nierhaus T, Vidaurre C, Sannelli C, Mueller KR, Villringer A. Immediate brain plasticity after one hour of brain-computer interface (bci). *J Physiol*. 2021;599(9):2435–2451. doi:10.1113/JP278118
50. Ortiz M, Ianez E, Gaxiola-Tirado JA, Gutierrez D, Azorin JM. Study of the functional brain connectivity and lower-limb motor imagery performance after transcranial direct current stimulation. *Int J Neural Syst*. 2020;30(8):2050038. doi:10.1142/S0129065720500380
51. Zhang Y, Qiu S, He H. Multimodal motor imagery decoding method based on temporal spatial feature alignment and fusion. *J Neural Eng*. 2023;20(2):26009. doi:10.1088/1741-2552/acbfdf
52. Moaveninejad S, D'Onofrio V, Tecchio F, et al. Fractal dimension as a discriminative feature for high accuracy classification in motor imagery eeg-based brain-computer interface. *Comput Methods Programs Biomed*. 2024;244:107944. doi:10.1016/j.cmpb.2023.107944
53. Shuqfa Z, Belkacem AN, Lakas A. Decoding multi-class motor imagery and motor execution tasks using Riemannian geometry algorithms on large eeg datasets. *Sensors*. 2023;23(11):5051. doi:10.3390/s23115051
54. Shuqfa Z, Lakas A, Belkacem AN. Increasing accessibility to a large brain-computer interface dataset: curation of physionet eeg motor movement/imagery dataset for decoding and classification. *Data Brief*. 2024;54:110181. doi:10.1016/j.dib.2024.110181
55. Hashem HA, Abdulazeem Y, Labib LM, Elhosseini MA, Shehata M. An integrated machine learning-based brain computer interface to classify diverse limb motor tasks: explainable model. *Sensors*. 2023;23(6):3171. doi:10.3390/s23063171
56. Arpaia P, Coyle D, Esposito A, et al. Paving the way for motor imagery-based tele-rehabilitation through a fully wearable bci system. *Sensors*. 2023;23(13):5836. doi:10.3390/s23135836

57. Muller GR, Neuper C, Pfurtscheller G. Implementation of a telemonitoring system for the control of an eeg-based brain-computer interface. *IEEE Trans Neural Syst Rehabil Eng*. 2003;11(1):54–59. doi:10.1109/TNSRE.2003.810423
58. Onishi A. Brain-computer interface with rapid serial multimodal presentation using artificial facial images and voice. *Comput Biol Med*. 2021;136:104685. doi:10.1016/j.compbiomed.2021.104685
59. Tong J, Xing Z, Wei X, et al. Towards improving motor imagery brain–computer interface using multimodal speech imagery. *J Med Biol Eng*. 2023;43(3):216–226. doi:10.1007/s40846-023-00798-9
60. An Y, Wong J, Ling SH. Development of real-time brain-computer interface control system for robot. *Appl Soft Comput*. 2024;159:111648. doi:10.1016/j.asoc.2024.111648
61. Nojima I, Sugata H, Takeuchi H, Mima T. Brain-computer interface training based on brain activity can induce motor recovery in patients with stroke: a meta-analysis. *Neurorehabil Neural Repair*. 2022;36(2):83–96. doi:10.1177/15459683211062895
62. Matarasso AK, Rieke JD, White K, Yusufali MM, Daly JJ, Mattia D. Combined real-time fMRI and real time fNIRS brain computer interface (bci): training of volitional wrist extension after stroke, a case series pilot study. *PLoS One*. 2021;16(5):e250431. doi:10.1371/journal.pone.0250431
63. Bundy DT, Souders L, Baranyai K, et al. Contralesional brain–computer interface control of a powered exoskeleton for motor recovery in chronic stroke survivors. *Stroke*. 2017;48(7):1908–1915. doi:10.1161/STROKEAHA.116.016304
64. Ferrero L, Quiles V, Ortiz M, Iáñez E, Gil-Agudo Á, Azorín JM. Brain-computer interface enhanced by virtual reality training for controlling a lower limb exoskeleton. *Iscience*. 2023;26(5):106675. doi:10.1016/j.isci.2023.106675
65. Panahi N, Amirani MC, Valizadeh M. An eeg-based brain-computer interface using spectral correlation function. *IEEE Access*. 2023;11:1. doi:10.1109/ACCESS.2023.3262465
66. Kaas A, Goebel R, Valente G, Sorger B. Topographic somatosensory imagery for real-time fMRI brain-computer interfacing. *Front Hum Neurosci*. 2019;13:427. doi:10.3389/fnhum.2019.00427
67. Zheng Y, Zhang D, Wang L, et al. Resting-state-based spatial filtering for an fnirs-based motor imagery brain-computer interface. *IEEE Access*. 2019;7:120603–120615. doi:10.1109/ACCESS.2019.2936434
68. Ieracitano C, Mammone N, Hussain A, Morabito FC. A novel multi-modal machine learning based approach for automatic classification of eeg recordings in dementia. *Neural Netwk*. 2020;123:176–190. doi:10.1016/j.neunet.2019.12.006
69. Bouton C. Cracking the neural code, treating paralysis and the future of bioelectronic medicine. *J Intern Med*. 2017;282(1):37–45. doi:10.1111/joim.12610
70. Wan Z, Li M, Liu S, Huang J, Tan H, Duan W. Eegformer: a transformer-based brain activity classification method using eeg signal. *Front Neurosci*. 2023;17:1148855. doi:10.3389/fnins.2023.1148855
71. Zhang Y, Liu D, Li T, Zhang P, Li Z, Gao F. Cgan-rirn: a data-augmented deep learning approach to accurate classification of mental tasks for a fnirs-based brain-computer interface. *Biomed Opt Express*. 2023;14(6):2934–2954. doi:10.1364/BOE.489179
72. Heo J, Park KS, Baek HJ, Chang MH, Pietro A, Aricò P. Enhancing the usability of brain-computer interface systems. *Comput Intell Neurosci*. 2019;2019(2019):1–12. doi:10.1155/2019/5427154
73. Yadav H, Maini S. Electroencephalogram based brain-computer interface: applications, challenges, and opportunities. *Multimed Tools Appl*. 2023;82(30):47003–47047. doi:10.1007/s11042-023-15653-x
74. Naufel S, Klein E. Brain-computer interface (bci) researcher perspectives on neural data ownership and privacy. *J Neural Eng*. 2020;17(1):16039. doi:10.1088/1741-2552/ab5b7f
75. Su J, Wang J, Wang W, et al. An adaptive hybrid brain-computer interface for hand function rehabilitation of stroke patients. *IEEE Trans Neural Syst Rehabil Eng*. 2024;32:2950–2960. doi:10.1109/TNSRE.2024.3431025