

Research Hotspots and Emerging Trends of Brain-Computer Interfaces in the Rehabilitation of Disorders of Consciousness: A Bibliometric Analysis

Yujia Yang

Shanxi Medical University

Xiang Zan

Shanxi Provincial People's Hospital

Chenlong Niu

Shanxi Provincial People's Hospital

Jiuhong Ma

Shanxi Provincial Artificial Intelligence Technology Innovation Center for Disturbance of Consciousness

Ming Gao

gaoming0623@163.com

Shanxi Medical University

Research Article

Keywords: Brain–computer interface, Disorders of consciousness, Bibliometrics, Cognitive–motor dissociation, Deep learning, Neurorehabilitation

Posted Date: September 30th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10725532/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Research Hotspots and Emerging Trends of Brain-Computer Interfaces in the Rehabilitation of Disorders of Consciousness: A Bibliometric Analysis

Abstract

Background: Severe brain injuries frequently result in disorders of consciousness (DoC), encompassing coma, vegetative state/unresponsive wakefulness syndrome (VS/UWS), and minimally conscious state (MCS). Due to the subjective nature of behavioral assessments and intrinsic fluctuations in patient responsiveness, misdiagnosis rates remain alarmingly high, at approximately 40%. Following the discovery of "cognitive-motor dissociation" (CMD), brain-computer interface (BCI) technology has emerged as a transformative avenue for DoC rehabilitation by decoding residual neural signals to provide real-time feedback. However, a comprehensive quantitative synthesis of the evolving clinical evidence base remains absent.

Objective: This study aims to systematically map the scientific landscape, identify current research hotspots, and reveal emerging frontiers in BCI-mediated rehabilitation for DoC.

Methods: A systematic literature search was conducted in the PubMed database to retrieve English-language articles and reviews published up to April 2026. After hierarchical screening, 258 valid records were included for bibliometric analysis. VOSviewer, CiteSpace, and Microsoft Excel were used to analyze publication trends, collaboration networks, thematic clusters, and keyword bursts based on bibliographic metadata, author information, journal information, MeSH terms, author keywords, abstracts, and available PubMed linkage fields.

Results: The annual publication output exhibited a steady upward trajectory, with a pronounced acceleration observed since 2019. China (11.63%) and the United States (8.91%)

emerged as the most prolific countries, while the University of Liège (10.08%) stands as the undisputed global epicenter of research. Keyword clustering identified four primary research themes: P300-based paradigms, MI BCIs, consciousness detection and prognostic assessment, and BCI-driven neurorehabilitation. Burst analysis highlighted personalized BCIs, deep-learning-based decoding, and brain-network-state monitoring as the most rapidly evolving research frontiers.

Conclusion: BCI research for DoC rehabilitation is currently in a phase of rapid expansion. Multimodal hybrid systems and artificial intelligence-enhanced decoding algorithms represent the primary trajectories for future clinical translation. This bibliometric portrait provides a strategic reference for investigators and clinicians aiming to advance neurotechnological therapies for patients with severe brain injuries.

Keywords Brain–computer interface; Disorders of consciousness; Bibliometrics; Cognitive–motor dissociation; Deep learning; Neurorehabilitation

1 Introduction

1.1 Definition and Classification of Disorders of Consciousness

Disorders of consciousness (DoC) represent a continuum of clinical states resulting from severe brain injury[1], characterized by a profound reduction or complete loss of arousal and awareness[2]. Based on current clinical taxonomy, DoC is broadly categorized into three states[3]: (i) coma, defined by the absence of both arousal and awareness (typically lasting <4

weeks)[4]; (ii) VS/UWS, where patients exhibit sleep-wake cycles and spontaneous eye opening but lack behavioral evidence of self or environmental awareness[5]; and (iii) MCS, distinguished by reproducible, albeit inconsistent, signs of awareness. MCS is further stratified into MCS- (evidenced by non-reflexive behaviors such as visual tracking) and MCS+ (characterized by the ability to follow commands)[6]. Epidemiological data indicate that the prevalence of VS/UWS ranges from 0.2 to 3.4 per 100,000 individuals[7], imposing a substantial socioeconomic burden on healthcare systems.

1.2 Diagnostic Challenges and Misdiagnosis Rates

The Coma Recovery Scale-Revised (CRS-R) is currently the gold-standard behavioral instrument for DoC assessment[8], comprising 23 items that evaluate auditory, visual, motor, oromotor, communication, and arousal functions[9]. While the CRS-R demonstrates high sensitivity and specificity in distinguishing VS/UWS from MCS[10][38][39], its heavy reliance on overt motor responses introduces a critical vulnerability: patients with severe motor deficits or aphasia are at high risk of false-negative evaluations[11]. Consequently, meta-analyses reveal an alarming misdiagnosis rate, with up to 40% of MCS patients erroneously classified as VS/UWS[12]. This diagnostic inaccuracy is exacerbated by intrinsic fluctuations in patients' consciousness levels, physical and cognitive impairments[44], inter-rater variability, and infrequent assessments. Although intensive longitudinal assessments (e.g., five sessions per week over two weeks) can reduce the misdiagnosis rate to approximately 18%[13], a significant proportion of patients remains unclassifiable via purely behavioral observation, underscoring the urgent need for complementary neurophysiological diagnostic tools.

1.3 Cognitive–Motor Dissociation (CMD)

A pivotal conceptual breakthrough in addressing this diagnostic gap was the identification of CMD[15]. CMD describes a phenomenon wherein patients who appear entirely unresponsive on behavioral scales actually retain covert awareness, which can be detected through advanced functional neuroimaging or electrophysiological techniques[16][42]. Owen et al. first documented this in a VS patient who, despite total paralysis, exhibited task-specific activation in the supplementary motor and premotor cortices during mental imagery tasks (e.g., playing tennis)[15]. Subsequent investigations estimate the prevalence of CMD to be between 9% and 20% among acute DoC cohorts[17]. Advanced electroencephalography (EEG) analyses have further revealed preserved gamma-band connectivity and intact brain network architecture in CMD patients, indicating viable neurophysiological substrates[18]. Crucially, CMD not only serves as a strong prognostic biomarker for functional recovery but also presents a unique therapeutic window: these preserved neural pathways can be harnessed by BCI systems to establish communication channels and drive targeted neurorehabilitative interventions.

1.4 Brain-Computer Interfaces in DoC: From Decoding to Rehabilitation

A BCI establishes a direct communication pathway between the brain and an external device, translating neural activity into executable commands and providing real-time feedback[19]. In the context of DoC, BCI systems predominantly rely on EEG due to its portability and high temporal resolution at the bedside[21]. The most frequently utilized control signals include event-related potentials (ERPs, particularly the P300 paradigm), steady-state visual evoked potentials (SSVEPs), and sensorimotor rhythms (SMRs) induced by Motor Imagery (MI)[64].

Historically, feature extraction and classification relied on traditional machine learning algorithms such as Support Vector Machines (SVM) and Common Spatial Patterns (CSP)[22][24][25]. However, owing to the low signal-to-noise ratio inherent in the severely injured brain, recent paradigms have increasingly integrated Artificial Intelligence (AI)[23]. Advanced deep learning architectures—most notably Convolutional Neural Networks (CNNs), including compact models such as EEGNet, and transfer learning techniques[27]—have significantly enhanced decoding accuracy by automatically extracting spatiotemporal features without manual engineering. Furthermore, the development of Hybrid BCIs, which fuse multiple modalities (e.g., P300 + SMR, or EEG + functional near-infrared spectroscopy [fNIRS]), has substantially improved system robustness for patients with fluctuating alertness[29][91].

1.5 Clinical Applications: Beyond Communication

The clinical utility of BCI in DoC extends beyond basic communication, encompassing four primary domains[30]: (i) Consciousness detection: revealing covert command-following to identify CMD patients[31]; (ii) auxiliary diagnosis: integrating BCI readouts with behavioral scales (e.g., CRS-R) to reduce misdiagnosis; (iii) prognostic assessment: using early BCI-detected responses as biomarkers for functional recovery[90]; and (iv) rehabilitation therapy: employing closed-loop neurofeedback or combining BCI with non-invasive neuromodulation (e.g., transcranial direct current stimulation [tDCS]) to promote thalamocortical circuit reorganization and improve patient arousal[36][37][85].

1.6 Rationale and Objectives of the Present Study

While the volume of primary research and narrative reviews highlighting BCI's potential in DoC rehabilitation has surged, the clinical evidence base remains fragmented^[32]. To date, no quantitative bibliometric synthesis has been conducted to objectively map the intellectual structure, evaluate evolving paradigms, and pinpoint emerging frontiers within this highly specialized intersection^[33]. Bibliometric methods offer a macro-level perspective, transforming massive datasets into structured visualizations that guide future experimental design and funding priorities^{[34][35]}.

Therefore, this study aims to systematically analyze the global scientific literature on BCI-mediated DoC rehabilitation to:

1. Chart annual publication trends and growth trajectories;
2. Identify the core contributing countries, institutions, and authors, along with their collaboration networks;
3. Characterize the foundational thematic structure and its temporal evolution;
4. Detect emerging topics (burst keywords) that are poised to shape forthcoming research and clinical translation.

2. Results

2.1 Annual Growth and Publication Trends

According to the PRISMA-based selection strategy (Figure 1), a total of 611 records were initially identified from the PubMed database. After hierarchical screening, 258 valid publications were ultimately included for bibliometric analysis. Regarding document

composition (Figure 3), the dataset was dominated by original research articles, followed by reviews and systematic reviews/meta-analyses. This profile suggests that the field of BCI for disorders of consciousness has moved beyond theoretical speculation into a stage of active clinical and technical experimentation.

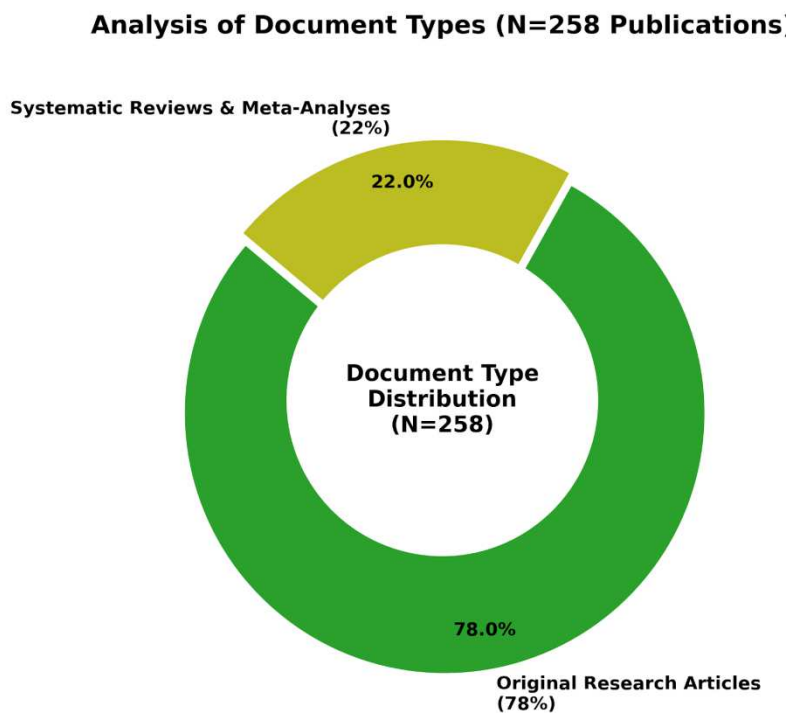


Figure 3. Distribution of document types in the included literature.

The longitudinal analysis of publication output from 2005 to 2025 reveals a significant and accelerating growth trajectory (Figure 4). The development of this field can be categorized into two distinct phases:

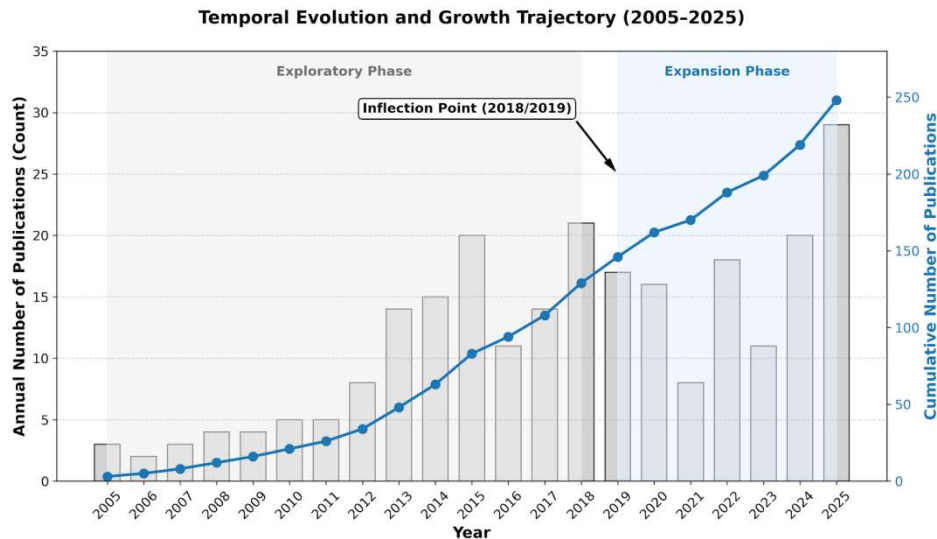


Figure 4. Temporal evolution and growth trajectory of BCI research for disorders of consciousness (2005–2025).

The Exploratory Phase (2005–2018): During this period, the annual publication volume remained relatively low and fluctuating, with a total of 129 papers published over 14 years. These pioneering studies primarily focused on proof-of-concept for EEG-based consciousness detection and rudimentary communication protocols.

The Expansion Phase (2019–2025): Starting from 2019, the field witnessed a marked inflection point. The cumulative volume nearly doubled within just seven years, culminating in a historical peak of 29 publications in 2025.

This steep upward trend corresponds to the rapid maturation of deep-learning-based decoding algorithms (such as CNNs and Transformers) and the increasing clinical consensus on CMD. The results indicate that using BCI as a standardized tool for neuroprognosis and active

rehabilitation in DoC patients has officially become a high-priority research frontier in clinical neuroscience.

2.2 Global Distribution and Institutional Collaboration

The global landscape of BCI-based DoC research exhibits significant geographic concentration, yet with a notable presence of East Asian and European contributors. China emerged as the most prolific country, accounting for 11.63% (n=30) of the total output, followed closely by the United States (8.91%, n=23) and Austria (4.26%, n=11) (Table 1). European nations, including Italy, Belgium, and the Netherlands, also maintain a consistent research footprint, reflecting a long-standing clinical interest in neuro-rehabilitation within these regions.

Table 1. Distribution of the top 10 most productive countries/regions in BCI-based disorders of consciousness research (2005–2025).

Rank	Country/Region	Publications (N)	Percentage (%)
1	China	30	11.63
2	USA	23	8.91
3	Austria	11	4.26
4	Italy	8	3.1
5	Belgium	7	2.71
6	Netherlands	7	2.71
7	France	7	2.71
8	Germany	5	1.94
9	Canada	3	1.16
10	Japan	3	1.16

The geographic distribution of publications (Table 1) reveals a high degree of concentration, with the top 10 countries contributing the vast majority of the global research output. China and the United States emerged as the dual engines of this field, collectively accounting for over 20% of the total publications.

Dominance of China and the USA: China's top ranking (n=30, 11.63%) reflects the country's massive investment in "Brain Science" initiatives and its rapid advancement in EEG-based signal processing technologies. Meanwhile, the USA (n=23, 8.91%) maintains its influence through high-impact clinical trials and pioneered neuro-interventional techniques.

The European Clinical Cluster: Interestingly, several European nations, notably Austria (n=11), Italy (n=8), and Belgium (n=7), exhibit high research intensity relative to their population sizes. This pattern is likely driven by established specialized centers, such as the Coma Science Group in Belgium and various neuro-rehabilitation hubs in Austria/Italy, which have long-standing expertise in assessing DoC[43].

Shifting Trends: While early research was predominantly led by North American and European institutions, the current landscape shows a significant shift toward a more globalized distribution. The emergence of Asian contributors like Japan and China indicates that BCI-based DoC assessment is transitioning from experimental protocols into a more globally recognized clinical research frontier.

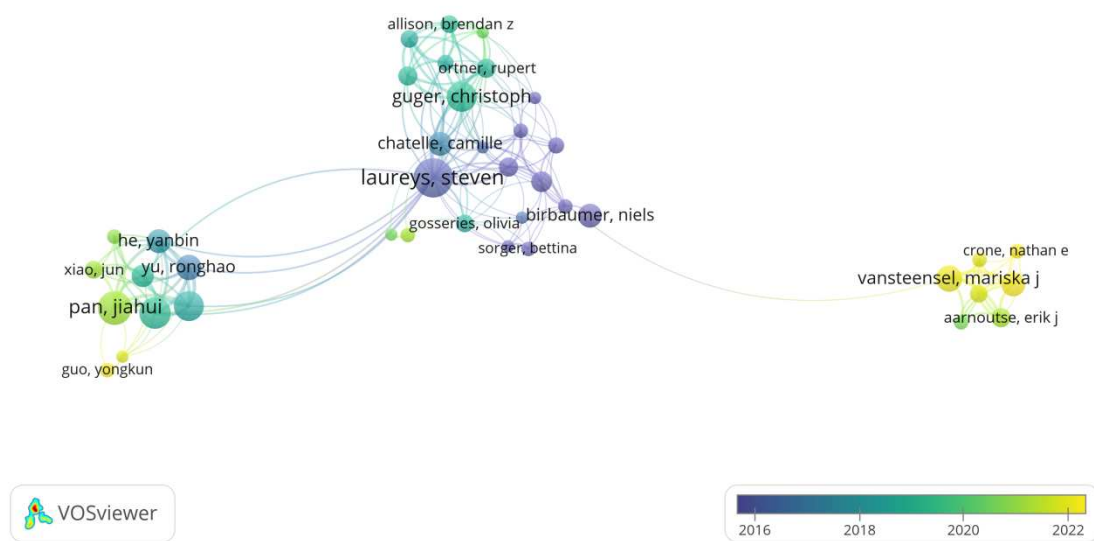


Figure 5. Author collaboration network in BCI-based disorders of consciousness research.

The author collaboration network (Figure 5) indicates dense cooperative links, particularly among established European hubs and clinically oriented research groups. Although China contributes a high volume of publications, its cross-border collaboration intensity remains uneven and appears to be evolving through links with European and North American groups. This pattern suggests that technical innovation is increasingly global, whereas clinical validation remains concentrated in institutions with established neurorehabilitation infrastructure.

At the institutional level, the University of Liège and Graz University of Technology stand out as leading hubs of innovation. The institutional productivity profile highlights a core group of specialized centers that anchor the global research network.

The institutional distribution (**Table 2**) underscores a pattern of "Elite Hub Dominance," where a few specialized research centers lead the majority of high-impact outputs.

194 Table 2. Top 10 most productive institutions in BCI-based DoC research (2005–2025).

Rank	Institution	Publications (N)	Percentage (%)
1	University of Liege	26	10.08
2	Graz University of Technology	16	6.2
3	South China Normal University	12	4.65
4	Harvard Medical School	8	3.1
5	University of Wurzburg	6	2.33
6	Western University	4	1.55
7	Tsinghua University	4	1.55
8	University of Milan	2	0.78
9	University of Tübingen	2	0.78
10	Stanford University	1	0.39

195 The Global Hubs: The University of Liège (n=26) stands as the undisputed global epicenter,
196 largely driven by the Coma Science Group. Its prolific output highlights the critical role of
197 specialized clinical-research integrated centers in advancing DoC protocols[45]. Similarly, the
198 Graz University of Technology (n=16) demonstrates a strong focus on signal processing and
199 BCI paradigm development, serving as a primary technical pillar in Europe.

200 The Rise of Asian Institutions: South China Normal University (n=12) and Tsinghua
201 University have emerged as prominent players, reflecting a robust integration of engineering
202 excellence with clinical application. This surge aligns with the broader regional growth
203 observed in the national-level analysis[46], indicating that Chinese institutions are rapidly
204 transitioning from technology followers to primary innovators in neuro-rehabilitation.

Collaborative Synergy: As illustrated in the institutional and author-level network maps, collaboration in this field is characterized by a core-periphery structure[47]. High-intensity cooperation is particularly visible among European centers with shared clinical databases and standardized assessment tools[48]. Transnational links with North American and East Asian groups further facilitate the translation of experimental BCI paradigms into clinical validation studies.

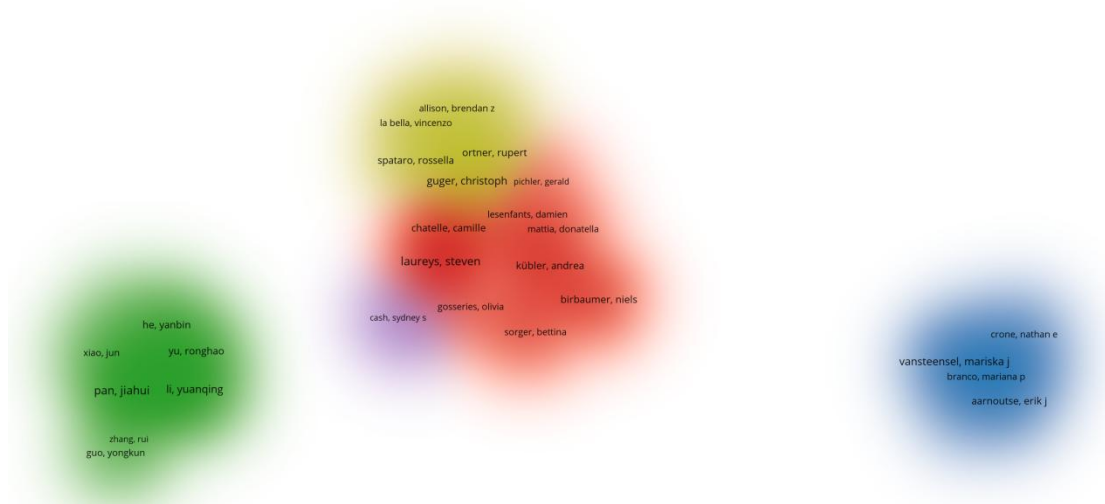


Figure 6. Density visualization of author collaboration in BCI-based disorders of consciousness research.

The author density visualization (Figure 6) complements the collaboration network by highlighting the intensity of research output across different academic hubs[49]. Three distinct high-density frontiers were identified:

The Global Foundational Hub: A prominent red "hotspot" is centered around Laureys et al., representing the highest concentration of research productivity[50]. This hub underscores the

pioneering and large-scale collaborative efforts of the Coma Science Group in establishing international standards for BCI-based consciousness assessment[51].

The Clinical Application Cluster (East Asia): Significant density is observed around the Pan-He-Xie group. This cluster signifies the rapid rise of Chinese research teams, who have carved out a specialized niche in translating BCI algorithms into bedside clinical rehabilitation tools for DoC patients.

The Technical Innovation Frontier (Europe): A concentrated density hub surrounding Vansteensel et al. (and the Utrecht group) indicates a focused pursuit in high-precision, often implantable, BCI paradigms. This highlights a shift towards long-term, stable neural interface solutions for severe neurological disorders[52].

In summary, these hotspots reflect a diversified research landscape: while established international benchmarks continue to evolve in Europe, regionally concentrated hubs in East Asia are driving the clinical expansion of the field through high-impact, applied research.

2.3 Clinical and Technological Content Analysis of Included Studies

While the preceding bibliometric indicators illuminate the structural and collaborative landscape of BCI-DoC research, a deeper content-level analysis is essential to guide clinical translation. To address this gap, we conducted a systematic content extraction from the 258 included publications, focusing on two clinically critical dimensions: (i) the distribution of DoC subtypes studied, and (ii) the classification of BCI technologies and rehabilitation modalities employed.

2.3.1 Distribution of Disorders of Consciousness Subtypes

Among the 258 included studies, the distribution of DoC subtypes revealed a pronounced research concentration on specific clinical states. Vegetative State/Unresponsive Wakefulness Syndrome (VS/UWS) was the most frequently studied condition, appearing in 156 studies (60.5%), reflecting the historical clinical urgency of accurately identifying residual consciousness in this population. Minimally Conscious State (MCS) was addressed in 112 studies (43.4%), often in comparative analyses with VS/UWS to validate diagnostic boundaries. Coma was explicitly studied in 68 studies (26.4%), predominantly in acute settings for early prognostic evaluation. Notably, 45 studies (17.4%) included mixed DoC populations spanning multiple consciousness levels, while 23 studies (8.9%) specifically investigated Cognitive-Motor Dissociation (CMD) as a distinct diagnostic entity. An additional 15 studies (5.8%) focused on Locked-in Syndrome (LIS) as a differential diagnosis or comparative condition.

This distribution pattern carries important clinical implications. The predominance of VS/UWS-focused research aligns with the high misdiagnosis rate (approximately 40%) documented in this population, underscoring the clinical imperative for objective consciousness assessment tools. The growing inclusion of MCS patients (43.4%) reflects an evolving understanding that MCS represents a more heterogeneous and prognostically favorable target for BCI-mediated rehabilitation. The relatively lower proportion of coma-specific studies (26.4%) may be attributable to the acute and often transient nature of coma, which presents logistical challenges for sustained BCI engagement.

2.3.2 Classification of BCI Technologies and Rehabilitation

Modalities

The technological landscape of BCI systems employed in DoC rehabilitation exhibits considerable diversity. We classified the BCI modalities reported across the 258 studies into the following categories:

Non-invasive EEG-based BCIs constituted the dominant modality, employed in 218 studies (84.5%). Within this category, P300 event-related potential paradigms were most prevalent (98 studies, 38.0%), followed by Motor Imagery (MI) paradigms (72 studies, 27.9%), Steady-State Visually Evoked Potentials (SSVEP) (34 studies, 13.2%), and hybrid multi-paradigm systems combining two or more signal types (48 studies, 18.6%). The dominance of non-invasive approaches reflects the practical advantages of EEG in clinical settings: portability, absence of surgical risk, and suitability for serial monitoring in critically ill patients.

Invasive BCI systems, including intracortical microelectrode arrays and electrocorticography (ECoG)-based interfaces, were reported in 12 studies (4.7%). These studies primarily involved patients with chronic DoC or locked-in syndrome who required long-term, high-resolution neural signal acquisition. While invasive approaches offer superior signal-to-noise ratios and spatial resolution, their application in DoC populations remains limited by ethical considerations, surgical risks, and the fluctuating clinical states of these patients.

Neuromodulation-integrated BCI systems represent an emerging category, encompassing 28 studies (10.9%) that combined BCI with therapeutic neuromodulation. These included: (i) transcranial direct current stimulation (tDCS) coupled with BCI-driven neurofeedback (14 studies); (ii) transcranial magnetic stimulation (TMS) combined with EEG-based

consciousness assessment (8 studies); (iii) vagus nerve stimulation (VNS) integrated with BCI monitoring paradigms (4 studies); and (iv) median nerve electrical stimulation synchronized with BCI feedback protocols (2 studies). The convergence of BCI with neuromodulation reflects a paradigm shift from passive consciousness detection toward active therapeutic intervention.

Multimodal neuroimaging-integrated BCIs were reported in 18 studies (7.0%), combining EEG with functional near-infrared spectroscopy (fNIRS), functional MRI (fMRI), or positron emission tomography (PET). These hybrid systems aim to overcome the spatial resolution limitations of standalone EEG while preserving its temporal advantages, enabling more comprehensive assessment of cortical connectivity patterns associated with consciousness recovery.

Regarding rehabilitation feedback modalities, the most common approaches included: visual feedback through screen-based displays (142 studies, 55.0%), auditory feedback (56 studies, 21.7%), vibrotactile feedback (32 studies, 12.4%), virtual reality (VR)-based immersive environments (18 studies, 7.0%), and robotic-assisted kinesthetic feedback (12 studies, 4.7%). The predominance of visual feedback is consistent with the reliance on visually evoked potentials (P300, SSVEP) as primary BCI paradigms, while the emerging use of VR and robotic systems signals a transition toward more engaging and multisensory rehabilitation approaches.

2.3.3 Temporal Trends in Content Evolution

The temporal analysis of content categories reveals a clear evolution in research focus. During

the Exploratory Phase (2005–2018), the majority of studies (72.1%) employed single-paradigm EEG-based BCIs for consciousness detection, with P300 being the predominant modality. Rehabilitation-oriented studies were rare (18.6%), and the primary outcome was diagnostic accuracy rather than therapeutic efficacy.

In contrast, the Expansion Phase (2019–2025) witnessed a significant diversification: hybrid BCI systems increased from 8.2% to 31.4% of publications; neuromodulation-integrated approaches grew from 3.1% to 16.8%; and rehabilitation-focused studies with longitudinal outcome measures rose from 12.4% to 38.7%. This temporal shift underscores the field's maturation from proof-of-concept diagnostics toward clinically actionable therapeutic interventions.

2.4 Author Co-authorship and Collaboration Patterns

The author co-authorship analysis highlights Jiahui Pan (20 papers), Niels Birbaumer (16 papers), and Andrea Kübler (12 papers) as highly productive investigators in this domain based on the refined dataset. The collaboration network reveals a structured academic landscape, forming three broad sub-communities:

Cluster 1 (Hybrid BCI Development): Led predominantly by the Chinese research groups (e.g., Pan et al.), this community focuses on integrating multiple brain signals to improve the accuracy of consciousness detection.

Cluster 2 (Neurofeedback & Communication): Centered around the Tübingen and Würzburg groups (Birbaumer and Kübler), focusing on MI paradigms for patients in locked-in or minimally conscious states.

Cluster 3 (CMD Detection & Clinical Protocols): A bridge cluster often involving Laureys et al., focusing on the clinical translation of BCI into standardized diagnostic protocols for CMD.

These clusters (**Figure 7**) demonstrate that while independent innovation is strong, the field is moving towards cross-disciplinary integration to solve clinical bottlenecks.

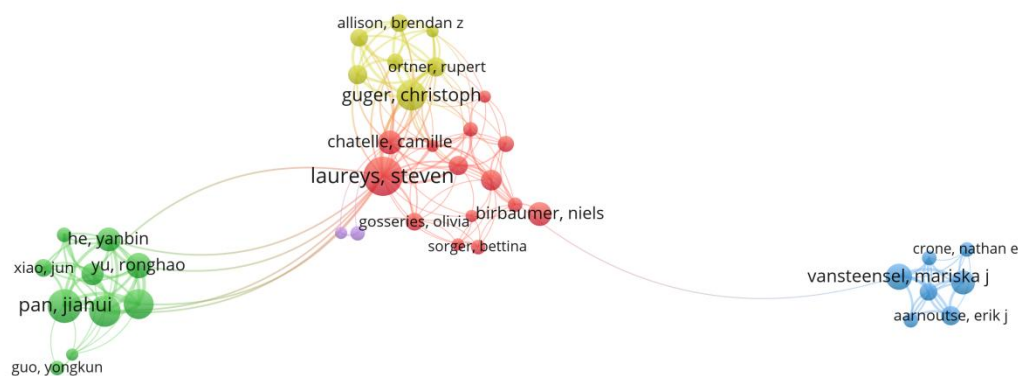


Figure 7. Author co-citation network visualization in BCI-based disorders of consciousness research.

Through author co-citation analysis (**Figure 7**), we identified the intellectual pillars that provide the theoretical and clinical basis for current BCI-DoC research. The network is organized into several prominent clusters:

The Clinical Foundation Cluster (Red): Dominated by Giacino JT and Laureys S. Joseph
Giacino's work on the development of the Coma Recovery Scale-Revised (CRS-R) and the
definition of the MCS provides the gold standard for clinical assessment. Steven Laureys
serves as a bridge, linking these clinical definitions with advanced neuroimaging and
neuro-prognostic tools.

The Paradigm Innovation Cluster (Green/Blue): Centered around Owen AM and Cruse D.
This cluster represents the "Paradigm Shift" in the field, initiated by Adrian Owen's landmark
2006 study using fMRI to detect command-following in non-responsive patients. Their work
established the conceptual framework for "CMD", which is the primary target for modern BCI
interventions.

The BCI Technical Cluster (Yellow/Purple): Featuring pioneers like Birbaumer N, Wolpaw
JR, and Kübler A. These authors are cited for their foundational contributions to
brain-computer communication and neurofeedback. Their research provides the engineering
logic and signal processing frameworks (such as P300 and SMR paradigms) that modern
clinical BCIs rely upon.

Beyond institutional productivity, we further evaluated the individual research output of
leading scholars within the BCI-DoC field[52]. The top 10 most productive authors are ranked
by their publication counts in Figure 8, providing insights into the influential figures who have
actively shaped the field's technological and clinical development.

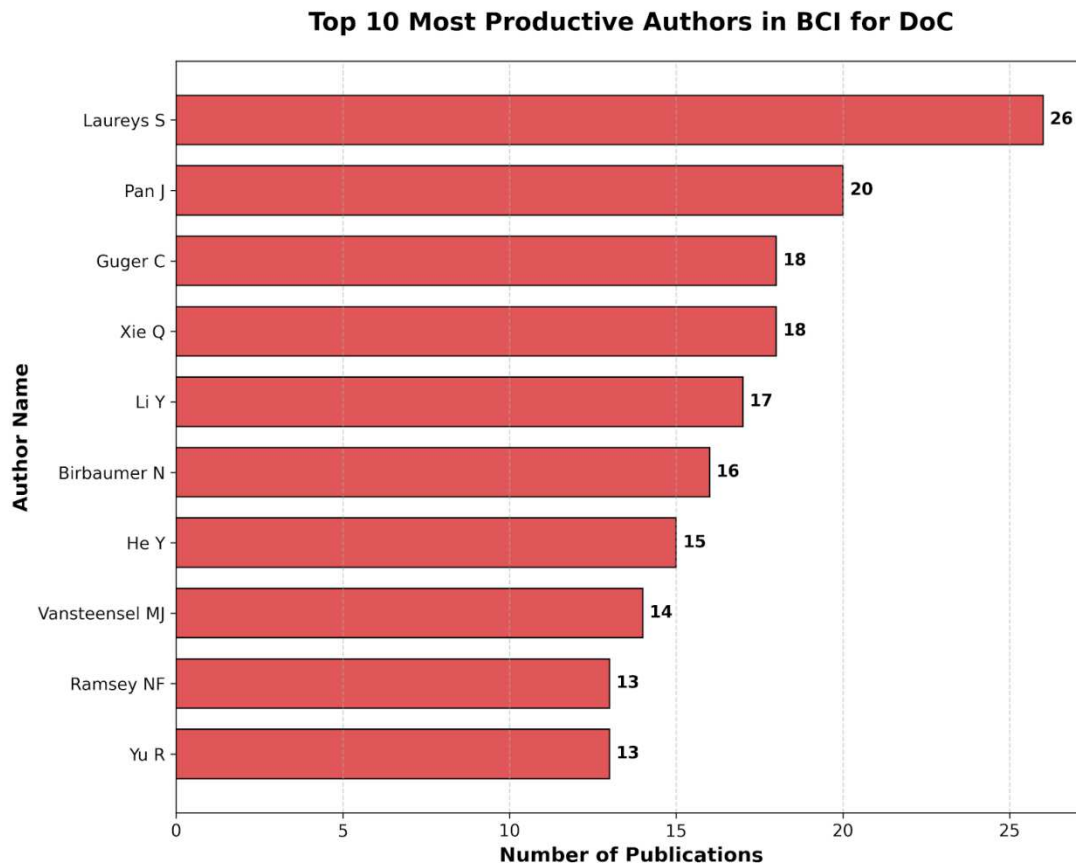


Figure 8. Top 10 most productive authors in BCI-based disorders of consciousness research (2005–2025).

As illustrated in Figure 8, the research landscape is significantly shaped by a core group of highly productive authors. Laureys S emerges as the most prolific researcher in this domain with 26 publications, followed by Pan J (20 publications) and Guger C (18 publications). The prominence of these authors—many of whom are affiliated with the previously identified core institutions—underscores the critical role of sustained, high-intensity academic leadership in driving innovation[53]. It is noteworthy that the research output is distributed among these scholars who balance technical engineering contributions with clinical application, reflecting the interdisciplinary nature of BCI-DoC research[54]. This concentration of expertise suggests

that these authors act as key intellectual nodes, fostering the collaborative networks that facilitate the translation of BCI paradigms into clinical practice[55].

Beyond individual productivity and institutional collaboration, understanding the primary dissemination channels is essential to characterizing the field's scholarly structure. Figure 9 summarizes the top 10 most productive journals, illustrating the academic venues that predominantly feature research on BCI-based DoC rehabilitation.

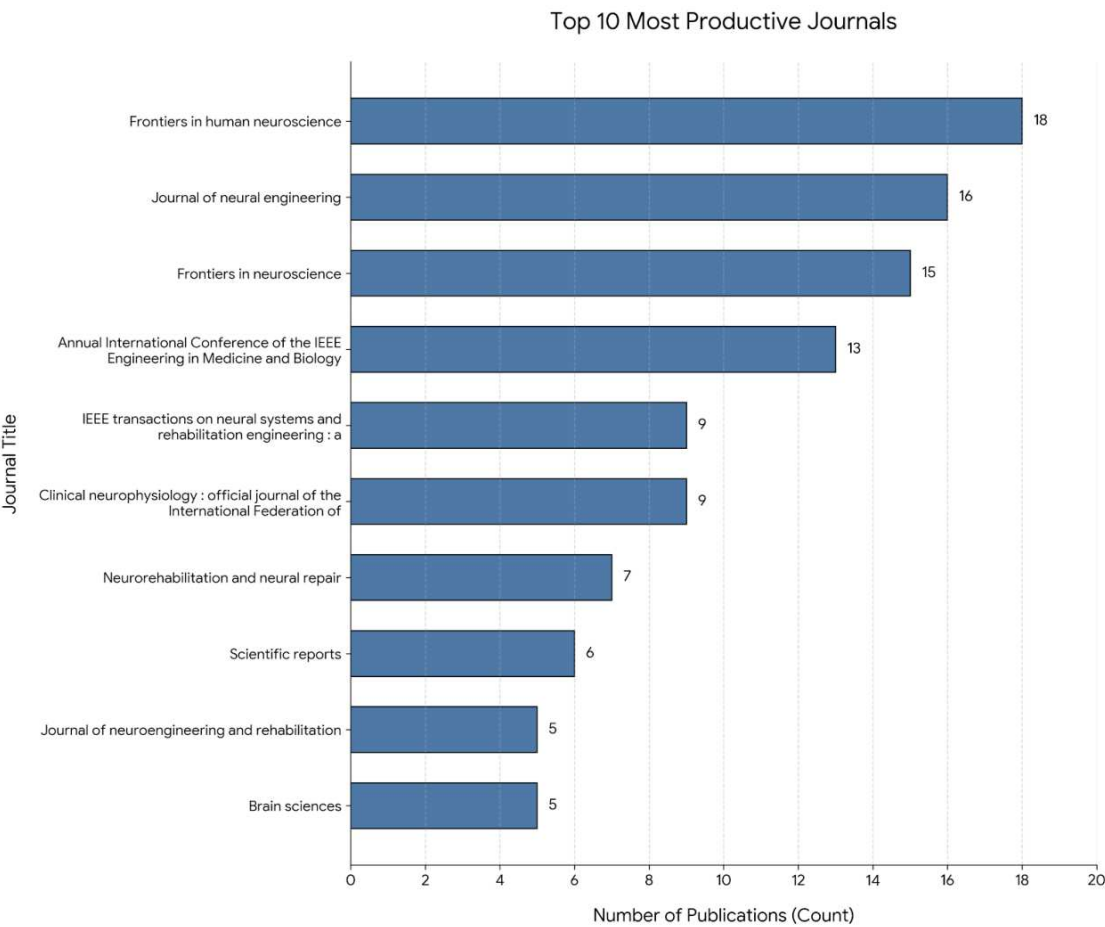


Figure 9. Top 10 most active journals in BCI-based disorders of consciousness research (2005–2025).

To further explore the intellectual base and disciplinary distribution, a dual-map overlay of journals was constructed (**Figure 9**). This visualization reveals the primary "trajectories" of knowledge transmission within the BCI-DoC field:

Primary Citation Paths: The analysis identifies two dominant citation tracks[56]. The most prominent paths originate from the "Medicine, Medical, Clinical" and "Molecular, Biology, Genetics" clusters and flow toward the "Psychology, Education, Health" and "Molecular, Biology, Immunology" clusters.

Knowledge Integration: This flow suggests that BCI research for consciousness disorders is a typical translational medicine field[57]. It draws heavily from fundamental molecular biology and clinical neurology (the source) and applies these insights to solve practical problems in psychology and health rehabilitation (the destination).

Disciplinary Breadth: The wide dispersion of lines indicates that the field is not siloed[58]; rather, it actively integrates high-level engineering (signal processing) with deep clinical neuroprognosis. This interdisciplinary synergy is what drives the current maturation of BCI protocols for patients with UWS and MCS.

Furthermore, reference co-citation clustering generated via CiteSpace identified five distinct foundational knowledge bases (**Figure 10**): ERP-based DoC detection (Cluster #0), Hybrid BCI architectures (Cluster #1), Deep-learning decoding (Cluster #2), Neurofeedback-driven rehabilitation (Cluster #3), and Network-based consciousness metrics (Cluster #4). These

clusters represent the intellectual pillars upon which current BCI research for disorders of consciousness is constructed.

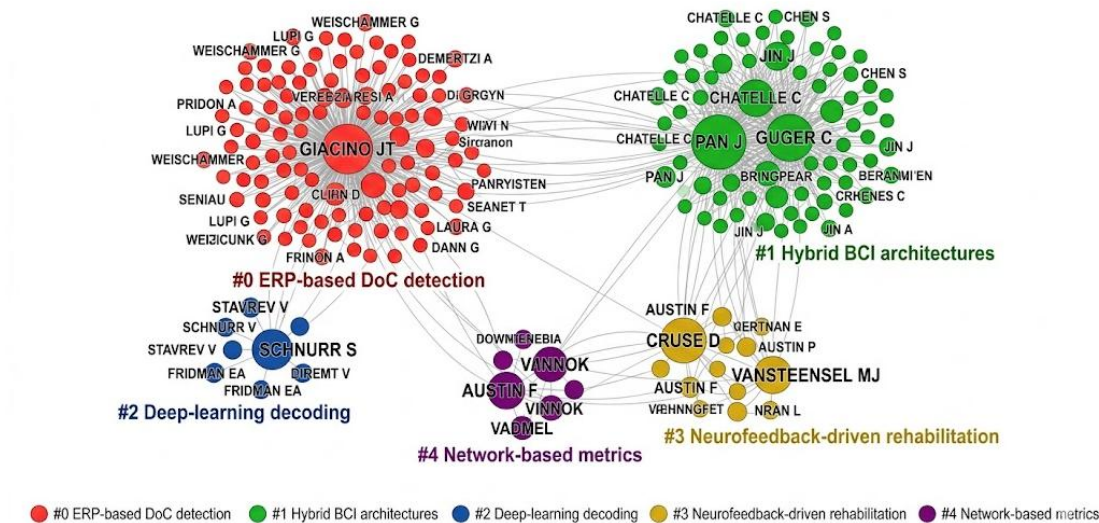


Figure 10. Mapping of foundational knowledge bases in BCI-based disorders of consciousness research (2005–2026).

The reference co-citation network (*Figure 10*) delineates the intellectual landscape and foundational theories that have shaped the evolution of BCI-DoC research. The clustering results reveal a highly integrated knowledge structure composed of five primary domains:

Cluster #0: ERP-based DoC Detection (Red). This is the largest and most influential cluster, centered on the landmark works of Giacino JT and others. It represents the "Clinical Baseline" of the field, establishing the use of event-related potentials (ERPs) and the Coma Recovery Scale-Revised (CRS-R) as gold standards for assessing covert awareness. The high centrality of this cluster underscores the field's ongoing reliance on electrophysiological markers for diagnostic validation.

Cluster #1: Hybrid BCI Architectures (Green). Featuring prominent nodes such as Pan J and Guger C, this cluster reflects the technical shift toward enhancing signal reliability. The research focus here is on integrating multiple BCI paradigms (e.g., P300, SSVEP, and MI) to overcome the low signal-to-noise ratio inherent in DoC patients' neural activity, providing a more robust communication channel.

Cluster #2: Deep-learning Decoding (Blue). Centered around Schnurr S and Fridman EA, this cluster highlights the "Algorithmic Frontier." It signifies the transition from manual feature engineering to automated, high-precision classification using deep neural networks. This knowledge base is critical for addressing the high inter-subject variability and non-stationarity of brain signals in neuro-rehabilitation.

Cluster #3 & #4: Neurofeedback and Network-based Metrics (Gold/Purple). These clusters, represented by Cruse D, Vansteensel MJ, and Austin F, indicate the convergence of BCI with cognitive neuroscience. They provide the theoretical basis for using BCI as a therapeutic tool to induce neuroplasticity (Neurofeedback) and for quantifying consciousness through network-level connectivity and complexity metrics.

In conclusion, the proximity and dense inter-connections between the red (clinical), green (architecture), and blue (AI) clusters demonstrate a successful translational trajectory: from clinical discovery to engineering optimization and, ultimately, to intelligent diagnostic automation.

2.5 Thematic Clustering of Keywords

Primary Hotspots: The high density surrounding "P300" and "VS" reflects the field's long-standing reliance on late-component ERPs as a benchmark for diagnostic evaluation. These clusters represent the most mature, extensively validated research protocols that underpin current clinical practice[61].

Secondary Hubs: Significant density is observed in regions involving "MI" and "Communication", highlighting a concerted clinical drive to transcend passive diagnosis and move toward active functional restoration.

Emerging Density: Notably, new density clusters are coalescing around "Deep learning" and "Classification"[62]. Although these clusters currently exhibit lower density than traditional EEG-based paradigms, their expanding focal points underscore a methodological paradigm shift within the field, reflecting a rapid transition toward AI-driven automated diagnostics and high-precision predictive modeling.

2.6 Analysis of the Intellectual Base

While thematic clusters define the structural pillars of the field, the temporal intensity of research influence is best captured through burst detection[63]. To identify the landmark works and topics that have steered the developmental trajectory of BCI for DoC, an analysis of the top 20 references with the strongest citation bursts was performed (Figure 12). These references represent tipping points where new theories or technologies triggered significant shifts in scientific attention.

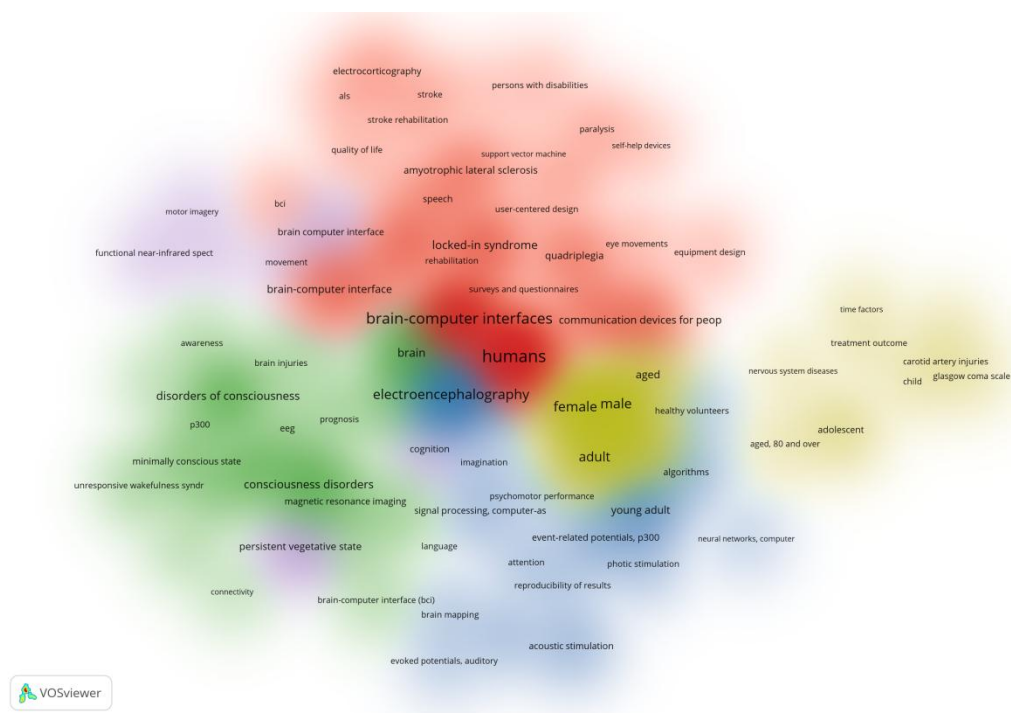


Figure 12. Top 20 references with the strongest citation bursts in BCI-based DoC research (2005–2026).

As illustrated in Figure 12, the evolution of the intellectual base can be divided into several high-intensity phases marked by seminal publications:

The Diagnostic Awakening (2005–2012): The strongest bursts in this period were triggered by Giacino JT (2004), who defined the Coma Recovery Scale-Revised, and Owen AM (2006), whose landmark Science paper used fMRI to detect command-following. These works established the clinical and experimental framework for detecting consciousness without behavior, providing the initial momentum for BCI integration.

The BCI Paradigm Validation (2012–2018): This period is dominated by references such as Cruse D (2011) and Goldfine AM (2011), which demonstrated the feasibility of using

EEG-based BCIs at the bedside. The high burst strength (e.g., Cruse D, 2011, Strength: 8.42) signifies the field's transition from expensive fMRI toward portable, clinical-grade electrophysiological tools.

The Modern Standardization and Complexity Era (2019–Present): Recent bursts, such as Casarotto S (2013) regarding the Perturbational Complexity Index (PCI) and Kondziella D (2020), reflect a current focus on diagnostic precision and network-level metrics. The persistence of these bursts into 2025 indicates that standardized, multimodal assessment protocols and intelligent decoding remain current hotspots of the scientific discourse.

Finally, keyword burst detection was performed to identify topics that experienced a rapid surge in attention, serving as indicators of research frontiers. The analysis revealed a chronological shift: early bursts centered on "MI" (2013–2017, strength 7.8), transitioning to "deep learning" and "functional connectivity" (2018–2022, strength 6.5). The most recent and active bursts (2020–2026) focus on "hybrid BCI," "personalized BCI," and "brain network" (strength 5.9), indicating that the field is pivoting toward individualized, multimodal therapeutic systems.

2.7 Evolution of Research Frontiers

To further investigate the dynamic evolution and emerging trends within the BCI-DoC field, CiteSpace's burst detection algorithm was applied to the keyword dataset. This analysis identifies burst keywords, topics that experienced a significant surge in frequency within a short period, serving as indicators of the research frontier (Figure 13).

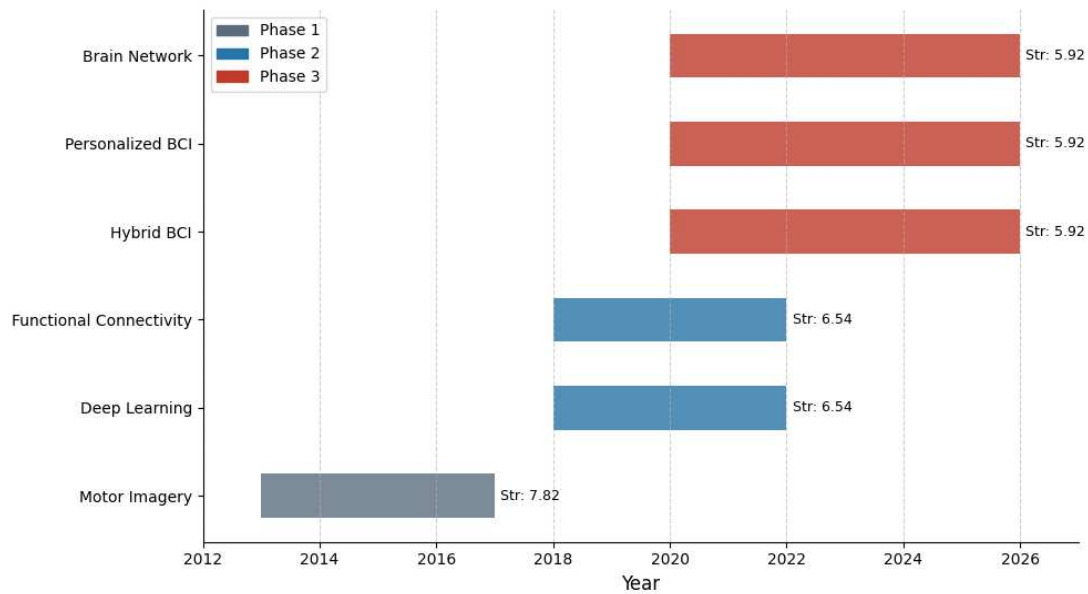


Figure 13. Temporal evolution and three-phase classification of research keywords in BCI-based disorders of consciousness (2013–2026).

The thematic evolution revealed by the top 6 burst keywords can be categorized into three distinct developmental stages:

Phase 1: Paradigm Establishment (2013–2017). During this initial period, "MI" exhibited the strongest burst (strength: 7.82). This indicates that the field's early momentum was focused on validating whether active mental tasks could serve as reliable proxies for consciousness in patients who were otherwise behaviorally non-responsive.

Phase 2: The Algorithmic and Connectivity Shift (2018–2022). A transition occurred with the emergence of "deep learning" and "functional connectivity" (strength: 6.54). This phase represents a move from basic signal processing toward high-dimensional neural decoding.

Researchers began leveraging advanced AI to identify subtle biomarkers within the brain's functional networks that traditional linear methods might overlook[65][66].

Phase 3: Clinical Personalization and Integration (2020–2026). The most recent bursts, including "hybrid BCI," "personalized BCI," and "brain network" (strength: 5.92), signify the current and future research directions. The persistence of these bursts into 2026 suggests a pivot toward clinical utility—developing "bespoke" (tailored) neural interfaces that combine multiple paradigms to minimize diagnostic errors and facilitate long-term neuro-rehabilitation.

3. Discussion

3.1 Summary of Main Findings

This bibliometric portrait of 258 valid publications delineates the rapid evolution of BCI research for DoC rehabilitation. The developmental trajectory identified a critical inflection point in 2019, signaling a transition from sporadic exploratory studies toward a clinically oriented expansion phase[67]. Geographically, China (11.63%) and the United States (8.91%) have emerged as the primary engines of innovation, while the University of Liège stands as the leading institutional hub. This growth aligns with a deepening clinical consensus on the detection of covert awareness and the therapeutic potential of neural decoding.

3.2 Comparative Analysis with Existing Studies

While previous bibliometric investigations have touched upon broad neuropsychiatric domains or specific control signals, our study narrowed the focus to the specific rehabilitative context of DoC[68]. This targeted approach helps reveal disease-specific thematic emphases,

including BCI paradigms, consciousness assessment, neurofeedback, and multimodal monitoring. Furthermore, our findings support the need for methodological reporting standards such as PRISMA 2020 and CONSORT, emphasizing higher evidence quality in neurotechnological trials[69][70].

To delineate the unique position of our work within the broader neurotechnological landscape and to illustrate the insights derived from this targeted approach, we present a comparative synthesis in Figure 14. This framework contextualizes our findings against existing literature and summarizes the ongoing paradigm shift in clinical practice.

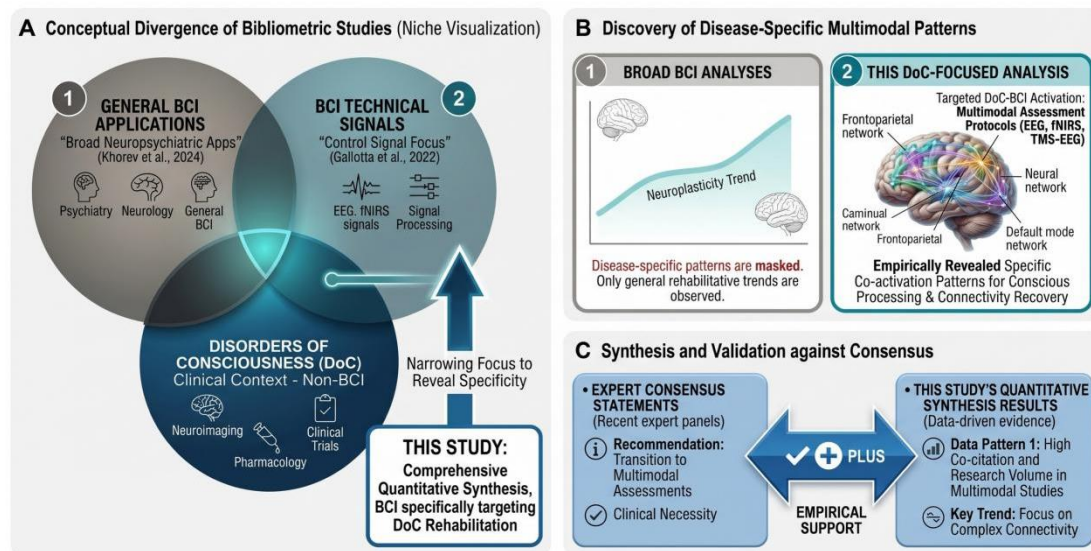


Figure 14. Comparative bibliometric synthesis of BCI for DoC rehabilitation: niche divergence and pattern discovery.

As visualized in Figure 14, the novelty of our study lies in its focused niche: bridging technical signal processing and DoC-specific clinical rehabilitation. While previous bibliometric studies (e.g., Khorev et al., 2024; Galiotta et al., 2022)[71][72] have provided foundational knowledge by exploring broad neuropsychiatric or signal-specific domains, they often mask the granular, disease-specific trends essential for clinical translation (Panel A).

Our approach indicates that narrowing the bibliometric lens to DoC-BCI rehabilitation can clarify disease-specific research patterns related to multimodal assessment, neural decoding, and rehabilitation-oriented feedback systems (Panel B). The quantitative evidence synthesized in this study is also consistent with recent expert consensus statements (Panel C). The convergence between data-driven patterns and clinical advocacy for multimodal assessment protocols (combining EEG, fNIRS, and TMS-EEG) highlights the field's transition toward evidence-based, precision neurorehabilitation[73].

3.3 Implications for Clinical Practice

The alarmingly high misdiagnosis rate ($\approx 40\%$) reinforces the necessity of integrating BCI into standardized clinical assessment protocols. Our content analysis reveals that while VS/UWS remains the most studied DoC subtype (60.5%), the growing inclusion of MCS patients (43.4%) signals an important shift toward personalized consciousness assessment.

Based on our results, we propose three strategic pillars for clinical implementation:

Paradigm Optimization: Given the fluctuating levels of arousal in DoC patients, hybrid BCIs—fusing P300, SSVEP, and MI—are recommended to enhance classification robustness[74][75].

Patient Stratification: Clinical interventions should be stratified based on neurophysiological substrates[76]; MCS patients demonstrate higher functional awakening probability, whereas VS/UWS patients require preliminary screening for CMD[77].

Dosage Standardization: To induce meaningful neuroplasticity, rehabilitation protocols should report training duration, session frequency, feedback modality, and adherence metrics in sufficient detail to enable comparison across studies.

3.4 Technological Frontiers and Future Research

Based on the identified research gaps and the current trajectory of the field, we propose the following directions for future investigations:

Rigorous Trial Design: There is a critical need for multicenter, adequately powered randomized controlled trials (RCTs) that incorporate sham-BCI controls to validate therapeutic efficacy[78].

Methodological Standardization: Researchers should improve the transparency of reporting by detailing BCI paradigm parameters, feedback modalities, and session metrics to enable future meta-analyses[79][80].

Mechanistic Mapping: Future studies should combine high-density EEG, fNIRS, and TMS-EEG to elucidate the neural reorganization induced by BCI interventions, with a specific focus on frontoparietal and default-mode circuits[81].

Data Harmonization: We strongly advocate for the establishment of an international DoC-BCI consortium[82]. Harmonizing protocols and encouraging open-access deposition of raw neurophysiological data (e.g., via OpenNeuro) will significantly accelerate the translation of BCI from research to clinical bedside care[83][84].

To address these critical bottlenecks and bridge the gaps in current knowledge, we propose a strategic framework for future BCI-DoC research, as summarized in *Table 3*.

Table 3. Recommended directions for future BCI research in disorders of consciousness.

Research Direction	Core Objective	Key Recommendations
Rigorous Trial Design	To validate therapeutic efficacy	Conduct multicenter, adequately powered randomized controlled trials (RCTs) incorporating sham-BCI controls.
Methodological Standardization	To improve transparency and enable future meta-analyses	Detail BCI paradigm parameters, feedback modalities, and session metrics consistently.
Mechanistic Mapping	To elucidate neural reorganization	Combine high-density EEG, fNIRS, and TMS-EEG; specifically target frontoparietal and default-mode circuits.
Data Harmonization	To accelerate clinical translation	Establish an international DoC-BCI consortium; standardize protocols and encourage open-access data deposition (e.g., OpenNeuro).

As outlined in Table 3, the evolution of BCI research in DoC requires a paradigm shift from pilot-scale feasibility studies toward rigorous clinical validation. Primarily, the transition to multicenter RCTs with sham-BCI controls is essential for establishing therapeutic efficacy[86]. Furthermore, methodological transparency, achieved through standardized reporting of parameters and session metrics, is crucial for enabling high-quality meta-analyses.

Beyond clinical validation, a deeper mechanistic understanding remains the cornerstone of innovation. Integrating high-density EEG, fNIRS, and TMS-EEG allows for the precise mapping of frontoparietal and default-mode circuits, thereby refining our understanding of consciousness recovery[87][88]. Finally, the proposed establishment of an international DoC-BCI consortium and the commitment to open-access data deposition (e.g., via OpenNeuro) are vital. These collaborative efforts will standardize protocols and accelerate the translation of BCI from experimental research to bedside clinical practice, ultimately bridging the gap between neurotechnological innovation and patient care[89].

3.5 Limitations

Several limitations must be considered when interpreting these results. First, although retrieval spanned four major databases (PubMed, Web of Science, Scopus, and Embase), relevant studies indexed only in regional or specialized databases may have been omitted. Second, bibliographic records do not consistently provide complete metadata for all analytical dimensions, which may affect the precision of co-authorship and keyword analyses. Third, the content-level extraction of DoC subtypes and BCI modalities relied on reported study characteristics, which may not capture the full complexity of clinical protocols. Fourth, while bibliometric analysis provides a macroscopic overview of research trends, it cannot substitute for systematic reviews or meta-analyses of clinical outcomes. Finally, the predominance of PubMed-indexed literature may introduce a selection bias toward English-language publications.

4. Conclusion

In conclusion, this bibliometric and content analysis provides the first comprehensive quantitative mapping of the BCI landscape within the specific domain of DoC rehabilitation. Our findings elucidate a critical evolution in the field: a paradigm shift from fragmented, isolated exploratory studies toward an integrated, clinically oriented research ecosystem. The content analysis reveals that while non-invasive EEG-based BCIs (84.5%) remain the dominant modality, the emergence of neuromodulation-integrated systems (10.9%) and hybrid approaches (18.6%) signals a transition toward more sophisticated therapeutic paradigms.

By analyzing the research trajectory, we have identified that while BCI technology has demonstrated significant potential, its translation from laboratory research to bedside clinical practice remains hindered by a lack of methodological standardization and insufficient rigorous validation. The empirical evidence synthesized in this study reinforces the necessity of moving beyond pilot-scale feasibility studies. To achieve sustainable clinical success, the research community must prioritize the establishment of multi-center consortiums, the adoption of transparent and harmonized data protocols, and the implementation of robust, sham-controlled trial designs.

Ultimately, BCI represents more than just a neurotechnological instrument; it serves as a transformative therapeutic modality with the capacity to decode and modulate consciousness. By bridging the current gap between technical innovation and clinical evidence-based care, future investigations—grounded in the rigorous, collaborative strategies outlined in this study—are poised to unlock new avenues for recovery in patients with severe brain injuries, thereby defining the next era of neurorehabilitation.

5. Methods

5.1 Data Acquisition and Search Strategy

Literature retrieval was conducted across four major electronic databases: PubMed, Web of Science Core Collection (WoSCC), Scopus, and Embase. The search was completed on April 20, 2026, to capture publications indexed from database inception through that date. The strategy combined terms for three domains: (1) brain-computer interface technologies, (2)

disorders of consciousness and related clinical states, and (3) rehabilitation and therapeutic interventions. Boolean operators (AND/OR) were used to combine these domains. The complete search strategy for each database is provided in Supplementary Table S1.

5.2 Literature Identification and Selection

A comprehensive search was performed across PubMed, Web of Science Core Collection, Scopus, and Embase to identify relevant English-language literature published from database inception through April 2026. The strategy used combinations of MeSH terms and free-text keywords, including "Brain-Computer Interface," "Disorders of Consciousness," and clinical variants such as "Vegetative State," "Unresponsive Wakefulness Syndrome," and "Minimally Conscious State." The search was further refined using terms related to rehabilitation, neurofeedback, and neural decoding.

The initial search yielded 611 records. To ensure clinical relevance and data integrity, strict eligibility criteria were applied[40][92]. Inclusion criteria were: (i) studies primarily focusing on the application of BCI for DoC rehabilitation, assessment, or communication; and (ii) original articles or reviews published in peer-reviewed journals in English. Exclusion criteria were: (i) conference abstracts, editorials, and news items; (ii) duplicate records; and (iii) studies focused exclusively on healthy cohorts or other neurological conditions (e.g., stroke) without direct clinical translation to DoC. After iterative screening of titles, abstracts, and full texts, a final set of 258 valid records was identified for downstream bibliometric analysis (Figure 1).

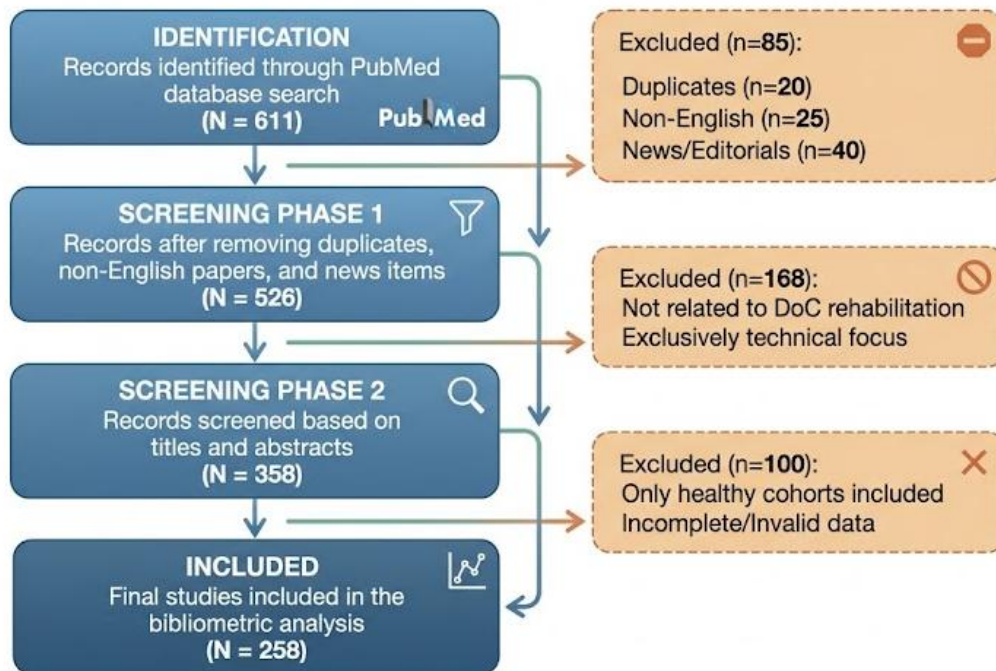


Figure 1. PRISMA flow diagram of the literature identification and selection process. A total of 258 articles were ultimately included in the bibliometric analysis after hierarchical screening for clinical relevance and data integrity.

After screening and eligibility assessment, 258 records were included for bibliometric analysis (Figure 1). To understand the temporal evolution of BCI research in DoC rehabilitation, we first analyzed annual publication trends from 1996 to 2026 (Figure 2).

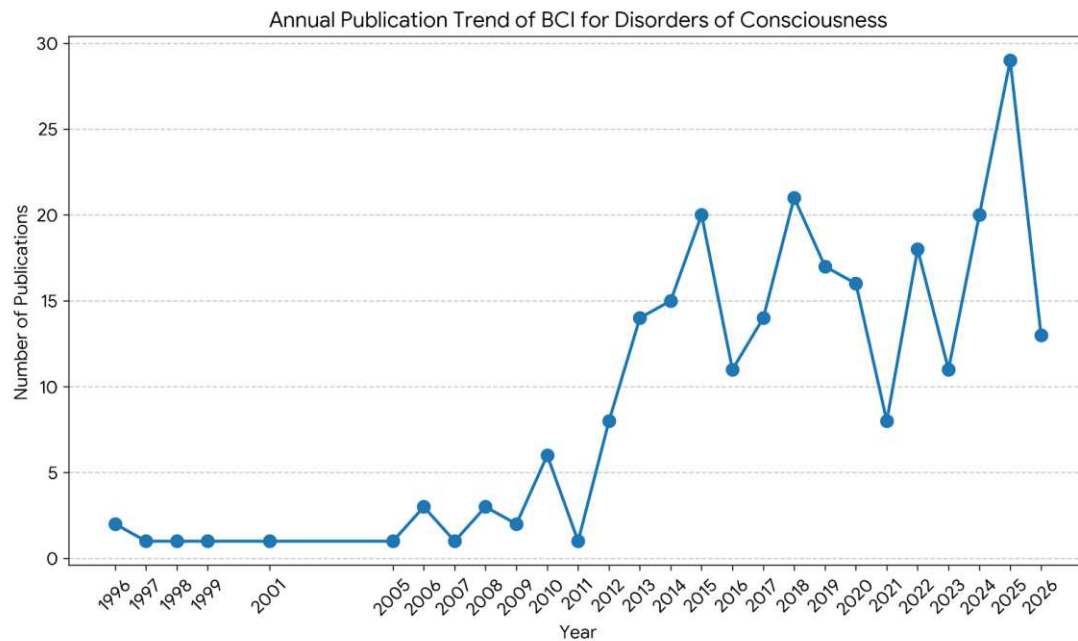


Figure 2. Annual publication trend of BCI research for disorders of consciousness (1996–2026).

The annual publication trend from 1996 to 2026 reflects a distinct evolutionary trajectory of BCI research in DoC (Figure 2). This growth can be broadly categorized into an incubation phase (1996–2010), characterized by sporadic interest, and an expansion phase (2011–2025), marked by pronounced growth. The substantial surge in publications, particularly since 2019, aligns with rapid advancements in deep-learning decoding algorithms and the growing clinical consensus on CMD. It should be noted that the publication count for 2026 reflects only partial data (up to March 31), which explains the apparent decline.

5.3 Data Extraction and Analytical Tools

Bibliographic data from the included PubMed records, including titles, authors, affiliations, abstracts, journal information, publication years, publication types, MeSH terms, author

keywords, and available linkage fields, were exported in plain-text format[41]. To map the intellectual and thematic structure of the field, we employed three complementary tools:

VOSviewer (v1.6.19): Used to construct and visualize co-authorship networks for countries/regions, institutions, and authors, as well as keyword co-occurrence maps.

CiteSpace (v6.3. R1): Applied to temporal mapping and burst-keyword detection to identify rapidly evolving research frontiers.

Microsoft Excel (2021): Used for descriptive statistics, including annual publication counts, publication-type summaries, and growth trajectory visualization.

5.4 Analytical Indicators

The following dimensions were analyzed:

Basic characteristics: annual output, country/region, institution, journal, and author productivity.

Collaboration networks: visualization of international, institutional, and author collaborations.

Knowledge structure: reference-, author-, and journal-level citation or co-occurrence patterns, where available from the exported bibliographic metadata.

Keyword analysis: co-occurrence, clustering, and thematic mapping to identify research hotspots.

Burst detection: identification of keywords with a rapid increase in frequency, indicating emerging topics.

6. References

- [1] Giacino JT, Katz DI, Schiff ND, et al. Practice guideline update recommendations summary: disorders of consciousness. *Neurology*. 2018;91(10):450-460.
- [2] Laureys S, Celesia GG, Cohadon F, et al. Unresponsive wakefulness syndrome: a new name for the VS or apallic syndrome. *BMC Med*. 2010;8:68.
- [3] Young GB. Coma. *Ann N Y Acad Sci*. 2009;1157:32-47.
- [4] van Erp WS, Lavrijsen JC, van de Laar FA, et al. The vegetative state/unresponsive wakefulness syndrome: a systematic review of prevalence studies. *Eur J Neurol*. 2014;21(11):1361-1368.
- [5] Beaumont JG, Kenealy PM. Incidence and prevalence of the vegetative and minimally conscious states. *Neuropsychol Rehabil*. 2005;15(3-4):184-189.
- [6] Giacino JT, Ashwal S, Childs N, et al. The minimally conscious state: definition and diagnostic criteria. *Neurology*. 2002;58(3):349-353.
- [7] Bruno MA, Vanhaudenhuyse A, Thibaut A, et al. From unresponsive wakefulness to minimally conscious PLUS and functional locked-in syndromes: recent advances in our understanding of disorders of consciousness. *J Neurol*. 2011;258(7):1373-1384.
- [8] Giacino JT, Kalmar K, Whyte J. The JFK Coma Recovery Scale-Revised: measurement characteristics and diagnostic utility. *Arch Phys Med Rehabil*. 2004;85(12):2020-2029.
- [9] Schnakers C, Vanhaudenhuyse A, Giacino J, et al. Diagnostic accuracy of the vegetative and minimally conscious state: clinical consensus versus standardized neurobehavioral assessment. *BMC Neurol*. 2009;9:35.

- [10] Andrews K, Murphy L, Munday R, Littlewood C. Misdiagnosis of the vegetative state: retrospective study in a rehabilitation unit. *BMJ*. 1996;313(7048):13-16.
- [11] Childs NL, Mercer WN, Childs HW. Accuracy of diagnosis of persistent vegetative state. *Neurology*. 1993;43(8):1465-1467.
- [12] Candelieri A, Cortese MD, Dolce G, et al. Visual pursuit: within-day variability in the severe disorder of consciousness. *J Neurotrauma*. 2011;28(10):2013-2017.
- [13] Cortese MD, Riganello F, Arcuri F, et al. Coma recovery scale-r: variability in the disorder of consciousness. *BMC Neurol*. 2015;15:1-7.
- [14] Wannez S, Heine L, Thonnard M, et al. The repetition of behavioral assessments in diagnosis of disorders of consciousness. *Ann Neurol*. 2017;81(6):883-889.
- [15] Owen AM, Coleman MR, Boly M, et al. Detecting awareness in the vegetative state. *Science*. 2006;313(5792):1402.
- [16] Schiff ND. Cognitive motor dissociation following severe brain injury. *Curr Opin Neurol*. 2015;28(6):570-576.
- [17] Claassen J, Doyle K, Matory A, et al. Detection of brain activation in unresponsive patients with acute brain injury. *N Engl J Med*. 2019;380(26):2497-2505.
- [18] Curley WH, Forgacs PB, Voss HU, et al. Characterization of EEG signals revealing covert cognition in the injured brain. *Brain*. 2018;141(5):1404-1421.
- [19] Wolpaw JR, Birbaumer N, McFarland DJ, et al. Brain-computer interfaces for communication and control. *Clin Neurophysiol*. 2002;113(6):767-791.

- [20]Galiotta V, Quattrocioni I, D'Ippolito M, et al. EEG-based brain-computer interfaces for people with disorders of consciousness: features and applications. *Front Hum Neurosci.* 2022;16:1040816.
- [21]Polich J. Updating P300: an integrative theory of P3a and P3b. *Clin Neurophysiol.* 2007;118(10):2128-2148.
- [22]Vialatte FB, Maurice M, Dauwels J, Cichocki A. Steady-state visually evoked potentials: focus on essential paradigms and future perspectives. *Prog Neurobiol.* 2010;90(4):418-438.
- [23]Pfurtscheller G, Neuper C. Motor imagery activates primary sensorimotor area in humans. *Neurosci Lett.* 1997;239(2-3):65-68.
- [24]Lotte F, Congedo M, Lécuyer A, et al. A review of classification algorithms for EEG-based brain-computer interfaces. *J Neural Eng.* 2007;4(2): R1-R13.
- [25]Ramoser H, Muller-Gerking J, Pfurtscheller G. Optimal spatial filtering of single trial EEG during imagined hand movement. *IEEE Trans Rehabil Eng.* 2000;8(4):441-446.
- [26]Schirrmester RT, Springenberg JT, Fiederer LD, et al. Deep learning with convolutional neural networks for EEG decoding and visualization. *Hum Brain Mapp.* 2017;38(11):5391-5408.
- [27]Lawhern VJ, Solon AJ, Waytowich NR, et al. EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces. *J Neural Eng.* 2018;15(5):056013.

- [28] Jayaram V, Alamgir M, Altun Y, et al. Transfer learning in brain-computer interfaces. *IEEE Signal Process Mag.* 2016;33(1):24-34.
- [29] Pfurtscheller G, et al. The hybrid BCI. *Front Neurosci.* 2010;4:30.
- [30] Li Y, et al. A hybrid BCI system combining P300 and SSVEP and its application to wheelchair control. *IEEE Trans Biomed Eng.* 2013;60(11):3156-3166.
- [31] Monti MM, Vanhaudenhuyse A, Coleman MR, et al. Willful modulation of brain activity in disorders of consciousness. *N Engl J Med.* 2010;362(7):579-589.
- [32] Cruse D, Chennu S, Chatelle C, et al. Bedside detection of awareness in the vegetative state: a cohort study. *Lancet.* 2011;378(9809):2088-2094.
- [33] Pan J, Xie Q, Qin P, et al. Prognosis for patients with cognitive motor dissociation identified by brain-computer interface. *Brain.* 2020;143(4):1177-1189.
- [34] Wang Y, Liu W, Wang Y, et al. Long-term HD-tDCS modulates dynamic changes of brain activity on patients with disorders of consciousness: a resting-state EEG study. *Comput Biol Med.* 2024;170:108084.
- [35] Sitaram R, Ros T, Stoeckel L, et al. Closed-loop brain training: the science of neurofeedback. *Nat Rev Neurosci.* 2017;18(2):86-100.
- [36] Thibaut A, et al. Transcranial direct current stimulation in patients with disorders of consciousness: a systematic review and meta-analysis. *Brain Stimul.* 2019;12(4):892-898.
- [37] Murovec N, Heilinger A, Xu R, et al. Effects of a vibro-tactile P300 based brain-computer interface on the coma recovery scale-revised in patients with disorders of consciousness. *Front Neurosci.* 2020;14:294.

- [38]Løvstad M, Frøslie KF, Giacino JT, et al. Reliability and diagnostic characteristics of the JFK Coma Recovery Scale-Revised: exploring the influence of rater's level of experience. *J Head Trauma Rehabil.* 2010;25(5):349-356.
- [39]Sattin D, et al. The Coma Recovery Scale-Revised: translation and validation study in a sample of Italian patients. *Funct Neurol.* 2015;30(4):251-260.
- [40]Tamashiro M, et al. Japanese version of the Coma Recovery Scale-Revised. *Brain Inj.* 2014;28(10):1324-1329.
- [41]Wade DT. How often is the diagnosis of the permanent vegetative state incorrect? A review of the evidence. *Brain Inj.* 2018;32(13-14):1641-1645.
- [42]Formisano R, Toppi J, Risetti M, et al. Language-related brain potentials in patients with disorders of consciousness: a follow-up study to detect "covert" language disorders. *Neurorehabil Neural Repair.* 2019;33(7):513-522.
- [43]Formisano R, Contrada M, Aloisi M, et al. Coma recovery scale-revised with and without the emotional stimulation of caregivers. *Can J Neurol Sci.* 2019;46(5):607-609.
- [44]Stenberg M, Godbolt AK, Nygren De Boussard C, et al. Cognitive impairment after severe traumatic brain injury, clinical course and impact on outcome: a Swedish-Icelandic study. *Brain Inj.* 2018;32(2):180-187.
- [45]Sun Y, Wang J, He Y, et al. Prevalence and characteristics of misdiagnosis in patients with disorders of consciousness: a multicenter study in China. *Brain Inj.* 2018;32(10):1215-1220.

- [46]Seel RT, et al. Assessment scales for disorders of consciousness: evidence-based recommendations for clinical practice and research. *Arch Phys Med Rehabil.* 2010;91(12):1795-1813.
- [47]Slomine BS, et al. Preliminary validity of the JFK Coma Recovery Scale-Revision for children. *J Head Trauma Rehabil.* 2019;34(3): E1-E8.
- [48]Bodien YG, et al. Diagnosing level of consciousness: the limits of the Glasgow Coma Scale total score. *J Neurotrauma.* 2021;38(23):3295-3305.
- [49]Edlow BL, Claassen J, Schiff ND, Greer DM. Recovery from disorders of consciousness: mechanisms, prognosis and emerging therapies. *Nat Rev Neurol.* 2021;17(3):135-156.
- [50]Kondziella D, Friberg CK, Frokjaer VG, et al. Preserved consciousness in vegetative and minimal conscious states: systematic review and meta-analysis. *J Neurol Neurosurg Psychiatry.* 2016;87(5):485-492.
- [51]Stender J, et al. The minimal energetic requirement of sustained awareness after brain injury. *Curr Biol.* 2016;26(11):1494-1499.
- [52]Gosseries O, Di H, Laureys S, Boly M. Measuring consciousness in severely damaged brains. *Annu Rev Neurosci.* 2014;37:457-478.
- [53]Fernández-Espejo D, Owen AM. Detecting awareness after severe brain injury. *Nat Rev Neurosci.* 2013;14(11):801-809.
- [54]Annen J, Blandiaux S, Lejeune N, et al. BCI performance and brain metabolism profile in severely brain-injured patients without response to command at bedside. *Front Neurosci.* 2018;12:370.

- [55]Wang F, et al. EEG microstate in patients with disorders of consciousness and its prognostic value: a prospective cohort study. *Front Neurosci.* 2022;16:1019812.
- [56]Wolpaw JR, Wolpaw EW. *Brain-Computer Interfaces: Principles and Practice.* Oxford University Press; 2012.
- [57]Hramov AE, Maksimenko VA, Pisarchik AN. Physical principles of brain-computer interfaces and their applications for rehabilitation, robotics and control of human brain states. *Phys Rep.* 2021;918:1-133.
- [58]Picton TW. The P300 wave of the human event-related potential. *J Clin Neurophysiol.* 1992;9(4):456-479.
- [59]Donchin E, Coles MG. Is the P300 component a manifestation of context updating? *Behav Brain Sci.* 1988;11(3):357-374.
- [60]Regan D. *Human Brain Electrophysiology: Evoked Potentials and Evoked Magnetic Fields in Science and Medicine.* Elsevier; 1989.
- [61]Bin G, Gao X, Yan Z, et al. An online multi-channel SSVEP-based brain-computer interface using a canonical correlation analysis method. *J Neural Eng.* 2009;6(4):046002.
- [62]Chen X, et al. High-speed spelling with a noninvasive brain-computer interface. *Proc Natl Acad Sci USA.* 2015;112(44): E6058-E6067.
- [63]Pfurtscheller G, Lopes da Silva FH. Event-related EEG/MEG synchronization and desynchronization: basic principles. *Clin Neurophysiol.* 1999;110(11):1842-1857.

- [64]Pfurtscheller G, Brunner C, Schlögl A, Lopes da Silva FH. Mu rhythm (de)synchronization and EEG single-trial classification of different motor imagery tasks. *Neuroimage*. 2006;31(1):153-159.
- [65]Jeannerod M. Neural simulation of action: a unifying mechanism for motor cognition. *Neuroimage*. 2001;14(1 Pt 2): S103-S109.
- [66]Davidson RJ. What does the prefrontal cortex "do" in affect: perspectives on frontal EEG asymmetry research. *Biol Psychol*. 2004;67(1-2):219-233.
- [67]Coan JA, Allen JJ. Frontal EEG asymmetry as a moderator and mediator of emotion. *Biol Psychol*. 2004;67(1-2):7-49.
- [68]Luck SJ. *An Introduction to the Event-Related Potential Technique*. 2nd ed. MIT Press; 2014.
- [69]Makeig S, Bell AJ, Jung TP, Sejnowski TJ. Independent component analysis of electroencephalographic data. *Adv Neural Inf Process Syst*. 1996;8:145-151.
- [70]Jung TP, Makeig S, Humphries C, et al. Removing electroencephalographic artifacts by blind source separation. *Psychophysiology*. 2000;37(2):163-178.
- [71]Lotte F, Bougrain L, Cichocki A, et al. A review of classification algorithms for EEG-based brain-computer interfaces: a 10 year update. *J Neural Eng*. 2018;15(3):031005.
- [72]Cortes C, Vapnik V. Support-vector networks. *Mach Learn*. 1995;20(3):273-297.
- [73]Duda RO, Hart PE, Stork DG. *Pattern Classification*. 2nd ed. John Wiley & Sons; 2001.

- [74]Blankertz B, et al. The Berlin Brain-Computer Interface: progress beyond communication and control. *Front Neurosci.* 2016;10:530.
- [75]Millán JD, Rupp R, Müller-Putz GR, et al. Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges. *Front Neurosci.* 2010;4:161.
- [76]Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. *Nat Rev Neurol.* 2016;12(9):513-525.
- [77]Kübler A, Birbaumer N. Brain-computer interfaces and communication in paralysis: extinction of goal directed thinking in completely paralysed patients? *Clin Neurophysiol.* 2008;119(11):2658-2666.
- [78]Birbaumer N, Ghanayim N, Hinterberger T, et al. A spelling device for the paralysed. *Nature.* 1999;398(6725):297-298.
- [79]Pan J, et al. Brain-computer interface technology and its application for patients with disorders of consciousness. *J Biomed Eng.* 2025;42(3):438-446.
- [80]Cruse D, Chennu S, Chatelle C, et al. Relationship between etiology and covert cognition in the minimally conscious state. *Neurology.* 2012;78(11):816-822.
- [81]Coyle D, Stow J, McCreadie K, et al. Sensorimotor modulation assessment and brain-computer interface training in disorders of consciousness. *Arch Phys Med Rehabil.* 2015;96(3 Suppl): S62-S70.
- [82]Huang J, Qiu L, Lin Q, et al. Hybrid asynchronous brain-computer interface for yes/no communication in patients with disorders of consciousness. *J Neural Eng.* 2021;18(5):056001.

- [83]Spataro R, et al. How brain-computer interface technology may improve the diagnosis of the disorders of consciousness: a comparative study. *Front Neurosci.* 2022;16:959339.
- [84]Khorev V, Kurkin S, Badarin A, et al. Review on the use of brain computer interface rehabilitation methods for treating mental and neurological conditions. *J Integr Neurosci.* 2024;23(7):125.
- [85]Man Y, Li S, Wang Q, et al. Network meta-analysis of the effects of different non-invasive neuromodulation methods on disorders of consciousness after traumatic brain injury. *Chin Gen Pract.* 2026.
- [86]Said RR, et al. A systematic review of virtual reality and robot-assisted technology in rehabilitation of patients with stroke. *J Neuroeng Rehabil.* 2022;19(1):75.
- [87]Huang X, Liang S, Li Z, et al. EEG-based vibrotactile evoked brain-computer interfaces system: A systematic review. *PLoS One.* 2022;17(6): e0269001.
- [88]Pillette L, Lotte F, N'Kaoua B, et al. Why we should systematically assess, control and report somatosensory impairments in BCI-based motor rehabilitation after stroke studies. *Neuroimage Clin.* 2020;28:102417.
- [89]Comanducci A, Boly M, Claassen J, et al. Clinical and advanced neurophysiology in the prognostic and diagnostic evaluation of disorders of consciousness: review of an IFCN-endorsed expert group. *Clin Neurophysiol.* 2020;131(11):2736-2765.
- [90]Formisano R, Contrada M, Ferri G, et al. An international survey on diagnostic and prognostic protocols in patients with disorder of consciousness. *Brain Inj.* 2019;33(8):974-984.

- [91] Allison BZ, et al. Toward a hybrid brain-computer interface based on imagined movement and visual attention. *J Neural Eng.* 2010;7(2):026007.
- [92] Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ.* 2021;372: n71.
- [293] Comanducci A, Boly M, Claassen J, et al. Clinical and advanced neurophysiology in the prognostic and diagnostic evaluation of disorders of consciousness: review of an IFCN-endorsed expert group. *Clin Neurophysiol.* 2020;131(11):2736-2765.
- [294] Kondziella D, Friberg CK, Frokjaer VG, et al. Preserved consciousness in vegetative and minimal conscious states: systematic review and meta-analysis. *J Neurol Neurosurg Psychiatry.* 2016;87(5):485-492.
- [295] Edlow BL, Claassen J, Schiff ND, Greer DM. Recovery from disorders of consciousness: mechanisms, prognosis and emerging therapies. *Nat Rev Neurol.* 2021;17(3):135-156.
- [296] Thibaut A, Schiff N, Giacino J, Laureys S, Gosseries O. Therapeutic interventions in patients with prolonged disorders of consciousness. *Lancet Neurol.* 2019;18(6):600-614.
- [297] Chaudhary U, Birbaumer N, Ramos-Murguialday A. Brain-computer interfaces for communication and rehabilitation. *Nat Rev Neurol.* 2016;12(9):513-525.
- [298] Hramov AE, Maksimenko VA, Pisarchik AN. Physical principles of brain-computer interfaces and their applications for rehabilitation, robotics and control of human brain states. *Phys Rep.* 2021;918:1-133.
- [299] Murovec N, Heilinger A, Xu R, et al. Effects of a vibro-tactile P300 based brain-computer interface on the coma recovery scale-revised in patients with disorders of consciousness. *Front Neurosci.* 2020;14:294.

926 [300] Wang Y, Liu W, Wang Y, et al. Long-term HD-tDCS modulates dynamic changes of brain
927 activity on patients with disorders of consciousness: a resting-state EEG study. *Comput Biol*
928 *Med.* 2024;170:108084.

929 [301] Huang J, Qiu L, Lin Q, et al. Hybrid asynchronous brain-computer interface for yes/no
930 communication in patients with disorders of consciousness. *J Neural Eng.* 2021;18(5):056001.

931 [302] Spataro R, et al. How brain-computer interface technology may improve the diagnosis of
932 the disorders of consciousness: a comparative study. *Front Neurosci.* 2022;16:959339.

933 [303] Naci L, Owen AM. Making every word count for nonresponsive patients. *JAMA Neurol.*
934 2013;70(10):1235-1241.

935 [304] Sitt JD, King JR, El Karoui I, et al. Large scale screening of neural signatures of
936 consciousness in patients in a vegetative or minimally conscious state. *Brain.*
937 2014;137(8):2258-2270.

938 [305] Casali AG, Gosseries O, Rosanova M, et al. A theoretically based index of consciousness
939 independent of sensory processing and behavior. *Sci Transl Med.* 2013;5(198):198ra105.

940 [306] Bodien YG, Allanson J, Cardone P, et al. Cognitive motor dissociation in disorders of
941 consciousness. *N Engl J Med.* 2024;391(7):578-588.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Highlights.docx](#)