Brain Monitoring Devices for Neuroscience: A Review of Current Technologies

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Abstract

This scoping review provides a technical characterization of 96 wireless brain monitoring devices (EEG and fNIRS), totaling 125 models and variants, currently available on the global market. A scientific characterization was performed by systematically searching the literature following PRISMA guidelines and registered in the OSF. The search was conducted across five databases (IEEE, Scopus, PubMed, Web of Science, and Embase) to identify the applications of the devices tracked in the market. The searches were conducted between January and August 2025. A total of 5,071 records were analyzed; 3,741 were unique entries. Among these, 2,087 studies explicitly reported the use of brain devices in clinical trials, dataset development, or technology evaluations, with an overall inclusion rate of 55.79\% after screening. Research adoption was quantified by the number of DOI-indexed publications referencing each device. The Epoc X leads the number of research publications with 19.30\%, followed by the OpenBCI system with 4.81\%, and the MindWave with 4.06\%. Enobio appears in fourth place with 2.89\% and g.Nautilus ranks eighth with 1.71\%. These findings demonstrate a global effort by researchers to conduct accessible studies using user-friendly, low-cost, and widely available devices, revealing a significant gap between consumer-grade and research-grade technologies. The compiled dataset provides an evidence-based framework to guide neuroscientists, engineers, and clinicians in selecting the appropriate device for their specific research needs. This work also identifies critical trends, such as the strong convergence toward wireless architectures and the growing emphasis on open data interfaces.

Keywords

Biomedical Instrumentation, Brain-Computer Interfaces, Electroencephalography (EEG), Functional Near-Infrared Spectroscopy (fNIRS), Wireless Neurotechnology.

Introduction

Advances in neurotechnology have profoundly transformed the field of neurorehabilitation, enabling targeted stimulation of neuroplasticity, data-driven clinical decision-making, and continuous monitoring of brain activity in both laboratory and real-world settings. These systems integrate sensor-based monitoring, signal processing, and computational modeling to generate objective indicators of brain function, enhancing the precision, reproducibility, and personalization of therapeutic interventions. The emergence of portable, wireless, and cost-effective brain monitoring devices has further democratized access to neuroscience tools, allowing the acquisition of high-quality neural data under ecologically valid and movement-rich conditions that better reflect functional behavior in daily life.

Among noninvasive neuroimaging modalities, electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS) have become fundamental in both clinical and experimental neuroscience. EEG records electrical potentials with high temporal resolution, providing direct insight into neuronal dynamics and oscillatory activity. Its portability, affordability, and compatibility with wearable architectures make it particularly suitable for neurofeedback and brain–computer interface (BCI) applications. In contrast, fNIRS measures hemodynamic changes associated with cortical activation by detecting oxygenation-dependent absorption of near-infrared light. Although it provides lower temporal resolution than EEG, fNIRS achieves higher spatial location and greater robustness against electrical interference. When combined, EEG and fNIRS offer complementary information—temporal precision and hemodynamic specificity—creating multimodal platforms capable of characterizing the neural mechanisms underlying movement, learning, and recovery.

In neurorehabilitation, these multimodal monitoring systems enable quantification of functional recovery and optimization of individualized therapy programs. They support closed-loop neurofeedback by providing brain-derived real-time metrics that guide adaptive training and promote cortical reorganization after neurological injury. When embedded in immersive or gamified environments, such systems enhance engagement and motivation, bridging neuroscience and rehabilitation engineering. The resulting datasets not only inform clinical decisions but also contribute to large-scale neurophysiological research through standardized and reproducible acquisition protocols.

Despite their growing potential, selecting the most appropriate brain monitoring device remains a major challenge. The commercial landscape has expanded rapidly, encompassing numerous manufacturers and models with heterogeneous technical specifications, including differences in signal quality, channel count, electrode or optode design, wireless architecture, data accessibility, and integration capabilities. This diversity, coupled with the absence of standardized technical reporting, hinders direct comparison between systems and complicates the alignment of device performance with specific experimental or therapeutic goals. As a result, decision-making often becomes complex and time-consuming, resembling the paradox of choice, where an excess of alternatives may obscure optimal selection.

To address this gap, the present work goes beyond existing wireless EEG and multimodal neurotechnology surveys by providing a large-scale, device-level mapping and technical characterization of commercially available EEG and fNIRS systems relevant to neuroscience and neurorehabilitation research. Unlike prior reviews that focus primarily on signal processing methods, experimental paradigms, or small subsets of devices, this study systematically analyzes 96 commercially available systems using manufacturer documentation, technical manuals, patents, and secondary literature. The resulting framework integrates engineering specifications with application-oriented criteria, including connectivity, data access, synchronization support, and proxy-based closed-loop readiness, as well as bibliometric indicators of device adoption in the literature. By combining technical, applicational, and adoption-level perspectives, this review offers a translationally oriented resource that is not available in existing surveys.

By integrating these dimensions, this review offers a decision-support framework to guide scientists, engineers, and clinicians in selecting brain monitoring technologies that are best suited to their methodological and operational requirements. Ultimately, its goal is to strengthen the interface between biomedical engineering and clinical neuroscience, accelerating the translation of portable brain monitoring systems into real-world neurorehabilitation contexts and advancing the development of evidence-based neurotechnological practice.

Background

Several studies have directly addressed the scope of this work, providing relevant findings and insights. According to [1], EEG remains a preferred modality in neuroscience and BCI research due to its widespread familiarity and high temporal resolution, which makes it particularly suitable for applications such as mental state classification, motor imagery, brain–computer interfaces, robotic control, and neuroadaptive games.

Reference [2] conducted a standardized comparison of six EEG systems, isolating signal quality from classifier performance. The active gel-based system achieved the highest signal-to-noise ratio (SNR), followed by a passive gel system, while other passive and dry electrode systems exhibited reduced performance because of design and contact limitations. The Saline-based electrodes showed the lowest signal quality. Despite lower SNR, wireless and dry systems are often favored in short-term or user-oriented contexts for their comfort and usability. For clinical or high-performance BCI applications, high-end systems remain the most reliable, though mid-range commercial devices may offer a cost-effective balance of signal quality and operational flexibility.

A study summarizes general technical specifications for six EEG devices and notes that several studies have empirically evaluated the effectiveness of these wearable neurotechnologies in fundamental research and BCI applications [3]. Reference [4] presents a comprehensive review of driver drowsiness detection systems, examining 24 EEG-based technologies that use physiological brain signals to determine drowsiness and wakefulness.

An overview of wireless EEG hardware is provided by [5]. This comprehensive survey includes 48 wireless EEG devices, outlining key features and specifications to enable side-by-side comparisons and support informed hardware selection. Additionally, it reviews 110 publications that employed wireless EEG, categorizing them by application and analyzing factors such as the devices used, number of channels, sample sizes, and participant mobility. Complementing this analysis, the paper provides background information and critical commentary on the challenges and considerations inherent to wireless EEG research, offering valuable insights.

As noted by [6], BCIs enable brain–device communication, typically via EEG. Common systems range from single-channel dry electrodes for targeted monitoring to saline-based devices offering broader functionality. Lightweight multichannel setups are preferred for comprehensive recordings, while headband-style devices are often used in gaming and sleep assessments. Dry electrodes are generally favored over wet ones due to reduced setup time and improved comfort. Device selection depends on the application and critical parameters such as sampling rate, resolution, battery life, and electrode count.

EEG devices are commonly categorized based on a combination of intended use, technical specifications, signal quality, and regulatory status, rather than a single criterion such as price or channel count. Consumer-grade EEG systems are generally low-cost, portable, and easy to deploy, and are primarily marketed for non-clinical applications such as neurofeedback, gaming, wellness, and exploratory experimentation. These systems typically feature a limited number of channels, prioritize usability and comfort, and often employ dry or semi-dry electrodes, which may constrain signal robustness. Research-grade EEG systems are designed for academic and laboratory use and provide higher channel counts, improved signal-to-noise ratio, flexible acquisition parameters, and full access to raw data, supporting rigorous experimental protocols. Clinical-grade (or medical-grade) EEG systems are certified for diagnostic and clinical applications and must comply with stringent regulatory standards for safety, reliability, and performance, including formal medical device approval. Overall, this classification reflects increasing levels of data quality, experimental control, and regulatory compliance across consumer, research, and clinical contexts [Chuang and Lin, 2019], [Doudou et al., 2020].

According to [7], wet-electrode EEG systems classified as research-grade or clinical-grade typically comprise 32 to 256 channels, cost tens of thousands of dollars, and offer high signal stability suitable for advanced analyses in controlled laboratory or clinical environments. However, these systems require trained personnel, setup times of approximately 15–30 minutes, and post-recording hair washing, which limits their usability outside laboratory settings. Despite these constraints, they provide scalable architectures and reliable access to raw signals, although the availability of embedded algorithms is often limited. In contrast, dry-electrode EEG systems, commonly associated with consumer-grade and some research-grade devices, are generally priced under a few thousand dollars, support 1 to 64 channels, and allow rapid setup (typically under 10 minutes) without the need for hair washing. These systems offer higher user comfort and wireless operation, enabling mobile and hyperscanning recordings, but may exhibit greater variability in signal stability.

From a signal quality perspective, consumer-grade EEG systems tend to perform adequately under high signal-to-noise ratio (SNR) conditions, such as event-related potential (ERP) paradigms conducted in controlled environments. However, their performance often degrades in real-world, low-SNR scenarios, particularly in mobile or naturalistic settings. Empirical evaluations indicate that research-grade systems, especially those with higher sensor density, yield more reliable and reproducible data under such conditions. These findings suggest that, despite their practical advantages, consumer-grade devices may be insufficient for studies requiring robust signal quality in ecological environments, underscoring the need for further advancements in dry-electrode technology to bridge this gap [8].

Reference [9] conducted a large-scale review of the technical specifications of 16 wireless EEG systems from multiple manufacturers. The study shows a comparative analysis of key features, underscoring the increasing accessibility and formal classification of wireless EEG technologies.

Another study [10] presents a table of 31 devices focused on measuring brain activity related to the central nervous system, highlighting key market players and their most representative products. Reference [11] classifies 22 brain monitoring devices based on their primary applications: executive function, psychomotor skills, and behavioral, emotional, and sensory domains. Study selection and analysis were systematically conducted following the PRISMA-ScR framework.

Reference [12] reports the development of a low-cost EEG system and compares commercial devices ranging from USD 300 to 50,000. High-end prices reflect regulatory certifications required for clinical use, which are often unnecessary for non-clinical BCIs. The limited availability of affordable, high-quality options leads researchers to rely on costly clinical-grade systems. As costs scale with channel count, reducing electrode number and optimizing spatial placement can improve cost-efficiency without compromising performance.

Passive EEG electrodes transmit signals directly to the amplifier, while active electrodes incorporate a preamplifier. Reliable recordings require stable electrode–scalp contact, shielding against electromagnetic interference, and consistent signal acquisition. Improved contact enhances noise identification and data reliability, potentially reducing the required sample size (n). Skin impedance decreases from \SI{\sim200}{\kilo\ohm} (uncleaned) to \SI{\sim120}{\kilo\ohm} (cleaned), with further reduction achievable through exfoliation or alcohol application at the electrode site [13].

Wet EEG electrodes with gel provide low impedance (\SI{<10}{\kilo\ohm}) but require skin preparation, electrolyte application, and cleaning. Signal quality declines as the gel dries, limiting its suitability for non-clinical use. Saline-based electrodes offer an alternative but may irritate abraded skin and promote oxidation, reducing lifespan [13], [14]. Dry electrodes enable faster setup; although impedance is higher, advanced algorithms reduce noise and artifacts. Well-designed dry systems combining optimized materials, placement, and shielding can achieve signal quality comparable to wet systems [14], [15], [16], [17]. Silver electrodes coated with silver chloride (Ag/AgCl) remain the gold standard due to their corrosion resistance [18].

Furthermore, low-cost EEG modules, typically compatible with open-source development platforms, have emerged as accessible alternatives for initial investigations, educational purposes, and non-clinical research. However, their limited functionality and susceptibility to noise constrain their use in high-precision applications [19].

The common-mode rejection ratio (CMRR) of driven right leg (DRL) circuits is essential for minimizing common-mode noise in biopotential recordings. DRL systems operate by inverting the common-mode voltage, detected via a common-mode sense (CMS) electrode, and feeding it back to the participant through the DRL electrode. This negative feedback reduces interference at the amplifier inputs, enhancing CMRR and signal fidelity. Combined, CMS and DRL improve noise rejection and overall recording reliability [20].

The lab streaming layer (LSL) enables precise multimodal synchronization without hardware triggers, supporting seamless integration with platforms such as MATLAB, Python, OpenViBE, BCI2000, and Unity. It synchronizes EEG, video, peripheral sensors, and stimulus markers for real-time applications, enhancing interoperability and scalability in research [21].

The fNIRS measures cortical oxygenation and blood flow up to \SI{\sim15}{\milli\metre} depth using red and near-infrared light. Emitted light penetrates the scalp and skull, interacts with brain tissue, and is detected by infrared sensors positioned a few centimeters away. Absorption patterns, influenced by changes in hemoglobin saturation, allow inference of cortical activity. Red light is primarily absorbed by oxygenated hemoglobin, while near-infrared light reflects total blood concentration. Short source–detector separations minimize contamination from superficial tissues, enhancing signal specificity [22].

Latency, response time, jitter, and throughput are key performance metrics in wireless EEG and fNIRS systems, influencing reliability and real-time operation. Latency is the delay from neural or hemodynamic activity to its digitized signal; response time adds processing delays. Jitter, or variability in these times, reduces temporal precision, while throughput, the rate of successful data transmission, often trades off with latency. Optimizing these metrics is essential for temporal resolution, data integrity, and real-time responsiveness [23], [24], [25], [26].

Brain monitoring devices increasingly integrate multimodal biosensors, including electrocardiography (ECG), photoplethysmography (PPG), pulse oximetry, and blood pressure for cardiovascular monitoring; electromyography (EMG) and electrooculography (EOG) for neuromuscular and ocular activity; and inertial measurement units (IMU), respiration sensors, and ballistocardiography (BCG) for motion and breathing. Galvanic skin response (GSR) and thermal sensors track skin conductance and temperature, while some systems add eye tracking and light-based neuromodulation, such as transcranial photobiomodulation (tPBM) and near-infrared photobiomodulation (NIR-PBM).

Method

This scoping review employed a structured documentary approach to identify and characterize commercially available brain-monitoring devices. Data were collected from both primary scientific literature and secondary sources, including patents, user manuals, and manufacturer websites. Devices were included based on the following criteria: (i) noninvasive neurotechnologies; (ii) portable form factor suitable for clinical or field use; (iii) commercial availability in the global market; (iv) sold as complete bundled systems rather than modular components; and (v) demonstrated or potential relevance to neuroscience and neurorehabilitation applications.

To define the technological scope of the review, MeSH categories were consulted. "Diagnostic Techniques and Procedures" was selected as the overarching classification encompassing brain-monitoring modalities across the target databases. Identified technologies included EEG, HEG, NIRS, fNIRS, PET, MEG, MRI, and fMRI. However, the final analysis focused exclusively on noninvasive, portable, and wireless EEG and fNIRS devices.

Database searches were conducted from March to August 2025 across five platforms: IEEE Xplore, PubMed/MEDLINE, Web of Science, Scopus, and Embase. Each search employed a Boolean query combining device name, manufacturer, and technology terms (e.g., "device" AND "manufacturer" AND "EEG/fNIRS"). Queries were adapted to the syntax and indexing structure of each database. IEEE Xplore was used for engineering and hardware design; PubMed/MEDLINE for its coverage of biomedical literature; Web of Science and Scopus for multidisciplinary indexing and citation tracking; and Embase for its emphasis on medical devices and international content.

An inclusion rate was used as a measure of search efficiency for each device-specific query. All retrieved records were screened to determine whether the named brain device was effectively applied as an experimental or clinical tool in the study; records in which the device name referred to an unrelated entity (e.g., personal names or acronyms with different meanings) or in which the device was merely mentioned without actual use were excluded. The inclusion rate was defined as the proportion of retrieved records that met the inclusion criterion of explicit device application, calculated as:

$$\textit{Inclusion rate} = \frac{\textit{Number of included studies using the device}}{\textit{Total number of records retrieved for that device}}$$

This metric reflects the precision of the device-specific search strategy, rather than sensitivity or recall, and was used to quantify the effectiveness of each query in identifying studies with confirmed device usage.

The number of DOI-indexed publications referencing each identified device was recorded to assess research use. No language or date restrictions were applied.

A summary table was compiled for all eligible devices, including technical parameters such as the number of channels, electrode type, sampling rate, data connectivity, software availability, and intended application. Additionally, peer-reviewed articles reporting experimental or clinical use of each device were identified to verify relevance, deployment, and impact across neuroscience and biomedical engineering domains.

The protocol of this scoping review was prospectively registered in the Open Science Framework (OSF) under the registration DOI: 10.17605/OSF.IO/EMRH8.

Results

A total of 5,071 records were retrieved from the selected scientific databases based on the inclusion criteria. After removing 1,331 duplicates (26.25\%), 3,741 unique records remained. Of these, 2,087 studies explicitly reported the use of brain monitoring devices in clinical trials, dataset development, or technological assessments, yielding an inclusion rate of 55.79\% after title, abstract, and full-text screening. Eighty records (2.14\%) were excluded due to a lack of access. Supplementary technical information was obtained from manufacturers' websites and consolidated in Table 1, comprising 96 devices, 125 when including model variants. Research adoption was quantified by the number of DOI-indexed publications referencing each device. No critical appraisal of individual sources of evidence was performed, as this scoping review aimed to map the extent and nature of the literature without assessing study quality.

Table 1. Portable and Wireless Brain Monitoring Devices (2025 Worldwide Commercial Availability)

Technology	Model	Type	Manufacturer	Origin	Brain Sensor	Sensor Tech Electrodes	Channels	Positioning	Wireless Connectivity	Sampling Rate	Resolution A/D	Raw Data	Software Provision	Software Sync	Auxiliary Capabilities	USD	Studies Found	%
EEG	Epoc X	Headset	Emotiv	USA	Wet (saline)	Saline soaked felt pads	14	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	BLE 4.0	128 / 256 Hz	14 bit	Requires PRO license	Included	SDK	IMU, Detects mental commands, performance states and facial expressions	>1,000	722	19,30%
EEG	Ganglion / Cyton / Daisy Ultracortex / Cap / cEEGrid	Headset / Cap / Around Ear	OpenBCI	USA	Hybrid (dry / gel) Semi Dry (saline) Wet (gel)	Ag/AgCl / Gold Cup / Gold plated C-shaped flex print	4 / 8 / 16	10-20 System	BLE 4.0	125 / 250 Hz	24 bit	Available	Open source	LSL	3x ExG, Analog In ExG, Digital I/O Trigger In/Out, Accelerometer	>1,000	180	4,81%
EEG	MindWave Mobile 2	Headset	NeuroSky	USA	Dry	Stainless steel	1	Fp1	Bluetooth SPP BLE/GATT	512 Hz	12 bit	Available	Free apps	TGC, SDK, TCP	—	>130	152	4,06%
EEG	Enobio	Cap	NE Neuroelectrics	ESP	Dry Wet (gel)	Drytrodes: Ag/AgCl coating Geltrodes: Sintered Ag/AgCl	8 / 20 / 32	Flexible 10-20 System	Wi-Fi	500 Hz	24 bit	Available	Free	LSL, TCP, SDK	Accelerometer, ERP, Hyperscanning, TTL triggers	—	108	2,89%
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Footnote. Closed-loop readiness represents a proxy-based classification of device suitability for real-time and closed-loop applications. This indicator is inferred from transmission-related specifications, including wireless communication protocol, channel count, nominal sampling rate, and data access capabilities. It does not reflect experimentally measured latency or jitter, nor does it imply regulatory certification or guaranteed real-time performance.

Table Description

Table 1 summarizes the technical, functional, and bibliometric characteristics of the EEG devices identified in this scoping review. The table reports the monitoring technology and commercial model, together with the device type, usage grade, manufacturer, and country of origin. The grade column classifies devices as consumer-grade, research-grade, or clinical-grade according to their intended use, technical capabilities, and regulatory context, providing a high-level distinction between wellness-oriented, research-focused, and clinically certified systems.

Sensor-related information includes electrode type and sensor technology, reflecting conductive media requirements, signal acquisition principles, and factors affecting signal quality, noise susceptibility, and user comfort. Hardware configuration is described by the number of recording channels and electrode positioning, while wireless connectivity specifies the communication technology used for data transmission.

Parameters relevant to data acquisition include the nominal sampling rate and analog-to-digital converter (ADC) resolution. Raw data access indicates whether unprocessed EEG signals are available to the user. Closed-loop readiness provides a proxy-based classification of device suitability for real-time and closed-loop applications, categorized as Low, Medium, or High, and inferred from transmission-related specifications, including wireless communication protocol, channel count, and nominal sampling rate. This classification supports a comparative assessment of real-time transmission constraints and performance trade-offs, without implying regulatory certification, experimentally validated latency or jitter, or guaranteed real-time performance. These proxy parameters reflect timing and bandwidth constraints relevant to closed-loop applications, such as real-time neurofeedback, adaptive BCI control, and event-locked multimodal synchronization.

Software-related aspects are reported through bundled software and data synchronization. Bundled software describes the availability and licensing model of manufacturer-provided software for data acquisition, control, or visualization, including desktop, mobile, web-based, or cloud applications, whether included, freely available, open-source, subscription-based, or sold separately. Data synchronization indicates the availability of software interfaces and communication protocols, such as SDKs, APIs, LSL, or TCP, that enable event-based and temporal alignment of EEG data streams with external systems or multimodal sources. Auxiliary capabilities summarize additional integrated functionalities, such as inertial sensors or embedded analytics.

Finally, price information, when available, is reported in U.S. dollars, excluding taxes and shipping, with currency conversion applied as needed; in cases where prices were not publicly disclosed, manufacturers were contacted, although such values are not shown to account for confidentiality and variability in purchasing terms. The bibliometric columns report the number of peer-reviewed studies using each device and the corresponding inclusion proportion, representing the share of included records in which the device was explicitly applied.

Device design varies substantially across categories. Caps streamline setup, enhance sensor contact, and optimize signal quality. Headsets, resembling headphones, combine ease of use with safety, making them suitable for immersive clinical and non-clinical scenarios. Headbands provide lightweight, ergonomic form factors ideal for cognitive research, neurofeedback, and brain-computer interfaces (BCI) in naturalistic environments. Earphones and headphones integrate auditory stimulation with EEG acquisition, while adhesive systems enable low-impedance, long-duration recordings, useful in intensive care unit (ICU) and sleep studies. The fNIRS caps and headsets offer spatial mapping of cortical activity and are used in complex cognitive and motor studies. Multimodal devices, including those integrating EEG with fNIRS, enhance spatial and temporal resolution, supporting applications such as virtual reality (VR)-based neurorehabilitation.

Discussion of Results

This review focuses on device-level technical specifications, reported capabilities, and usage patterns across the literature, rather than on experimental validation of signal quality or performance benchmarking under controlled conditions. As validation protocols, signal-to-noise ratios, and comparative performance metrics are highly task-, setup-, and population-dependent and are inconsistently reported across studies, a quantitative cross-device evaluation of signal quality was considered outside the scope of this scoping review. Instead, performance trade-offs between devices were examined at an architectural and applicational level, considering factors such as channel count, electrode technology, wireless communication protocol, data access, and software integration.

The 125 devices identified in this work span an impressive range of channel counts, from ultra-compact single-channel units designed for basic biofeedback to full 150-channel research-grade rigs. Counts in the studies found column indicate not only device popularity but also empirical maturity, reflecting the availability of reliable estimates for signal-to-noise ratio (SNR), noise spectral profiles, dropout rates, and operational parameters such as typical impedance, setup time, and gain/analog-to-digital converter (ADC) stability. Devices with extensive literature typically exhibit well-characterized sensor geometries and analog front-ends, enabling informed technical decisions on montage, preprocessing (bandpass, notch, referencing), artifact modeling (ICA templates, motion regression), and synchronization requirements for ERP or closed-loop paradigms. However, a high publication count does not eliminate methodological risks: firmware or driver updates, raw data access policies, and reliance on proprietary pipelines may introduce systematic biases and affect inter-site reproducibility. These factors require authors to report the firmware version and exact acquisition conditions.

Some models are frequently cited (often due to accessibility and cost), while others show few or no reported applications, indicating a lack of independent validation. For studies requiring statistical robustness and reproducibility (e.g., clinical ERP, connectivity analyses), selecting devices with substantial prior use reduces measurement bias risk. In exploratory or prototyping contexts, devices with limited publications may still be valuable if accompanied by technical validation (pilot SNR, dropout, latency) and explicit discussion of generalization limits, as low study counts may reflect novelty or barriers such as cost, licensing, or raw data availability.

Sampling rates across these devices reflect their intended applications. Consumer-grade and low-power BCI headsets often operate at 86–250 Hz, sufficient for basic cognitive and affective studies. Most research-oriented systems, however, sample between 250 Hz and 1 kHz, supporting standard ERP, spectral, and time–frequency analyses without aliasing. A few multimodal platforms push sampling rates up to 16 kHz to capture high-frequency EEG or evoked potentials with millisecond precision, though this comes with increased demands for data storage and transmission.

Bit depth is another critical differentiator. Lower-cost units typically employ 12–14-bit ADCs, adequate for classroom demonstrations or basic neurofeedback. Mid-tier research systems almost universally provide 16-bit resolution, offering a robust SNR for most experimental paradigms. Premium devices feature 24-bit or even 32-bit converters, minimizing quantization noise and maximizing dynamic range for detecting subtle oscillatory phenomena or conducting source localization.

Connectivity options mirror trade-offs between mobility and data throughput. Bluetooth dominates the entry and mid-range segments, enabling wireless operation at sampling rates up to 1 kHz with latencies suitable for BCI control or ambulatory monitoring. A smaller subset of systems supports Wi-Fi streaming, which is essential for multi-subject experiments (hyperscanning).

This scoping review focuses on device-level technical specifications and adoption patterns reported in the literature, rather than on clinical validation or experimental benchmarking of signal quality.

Latency, jitter, and throughput were not reported as device-specific numerical values, as these metrics are rarely disclosed by manufacturers and are highly configuration-dependent. In this review, these parameters are therefore treated as application-level performance criteria, rather than experimental measurements, and were integrated into the comparative framework using protocol- and data-rate–based proxies. Throughput requirements were inferred from channel count and nominal sampling rate, while latency and jitter were contextualized according to the wireless communication protocol. In this context, quantitative integration refers to the use of minimum data-rate requirements and protocol-level constraints as comparative proxies, rather than to experimentally measured latency or jitter values.

Software support is a major consideration beyond hardware specifications. Approximately 70–80\% of devices include their own acquisition and visualization suites; more advanced systems supplement this with Python, MATLAB, or LabVIEW SDKs, enabling custom preprocessing, real-time artifact rejection, and precise synchronization with stimuli or other biosignals. Entry-level headsets may only permit audio-based triggers or manual markers, adequate for broad cognitive tasks but insufficient for high-precision studies or closed-loop neuromodulation.

Based on a renowned manufacturer whose devices are widely recognized in research, the cost of EEG systems varies significantly with the number of channels, which directly affects spatial resolution and the range of clinical or research applications. Lower-channel systems, such as 8-channel devices, are priced around \$6,000 (USD), making them suitable for basic monitoring tasks, educational use, or preliminary research. As channel count increases, so does the system's complexity and capabilities, resulting in higher costs. For instance, a 16-channel EEG device is priced at approximately \$14,000, while a 32-channel system costs about \$24,000. High-density EEG systems with 64 channels offer superior spatial resolution and advanced signal acquisition but are substantially more expensive, often exceeding \$50,000. These price differences highlight the trade-offs between cost, signal quality, and application scope, underscoring the importance of selecting a system that aligns with the project's specific needs and budgetary constraints.

Regarding devices with electrode caps, the choice of base material is critical. Densely woven meshes and thick fabrics, such as neoprene, may cause discomfort due to increased scalp pressure and heat retention, given the head's sensitivity to temperature variations. Excessive or uneven pressure can degrade signal quality by affecting the electrode–skin interface, increasing impedance, and introducing motion artifacts. Furthermore, sustained pressure may lead to thermal discomfort and sweating, which can further impair conductivity. Asymmetrical pressure distribution may also introduce artificial asymmetries in the recorded data. Consequently, device design must prioritize ergonomic fit and material selection to ensure user comfort while preserving signal integrity and data reliability.

The “Epoc X” device by Emotiv leads the number of research publications with 19.30\%, followed by the OpenBCI system with 4.81\%, and the “MindWave Mobile 2” by Neurosky with 4.06\%. All three are consumer-grade models. In fourth place appears the first research-grade device, the Enobio by Neuroelectrics, with 2.89\%. The g.Nautilus by g.tec ranks eighth, representing 1.71\% of usage in published research.

These findings demonstrate a global effort by researchers to conduct accessible studies using user-friendly, low-cost, and widely available devices, revealing a significant gap between consumer-grade and research-grade technologies.

In summary, most rehabilitation-oriented neuroscience studies will find an optimal balance in 16 to 32-channel devices sampling at 1 kHz with 16-bit resolution, Bluetooth streaming, and a user-friendly SDK. For laboratories with greater demands for spatial resolution or multimodal recording, premium systems—though more expensive and operationally demanding—offer unparalleled data quality and flexibility. By understanding how hardware and software parameters interact, researchers can select a brain monitoring system that best balances spatial coverage, signal fidelity, mobility, and cost to meet their specific investigative goals.

Limitations of Technologies Evaluated

The technologies applied in brain research have been fundamental in enhancing our understanding of the nervous system and in developing interventions for neurorehabilitation. However, their use comes with several limitations that can impact their effectiveness, applicability, and reach across different contexts. These limitations span technical, economic, and operational aspects, all of which must be carefully considered in the development and implementation of these tools.

From a technical perspective, key challenges include resolution, accuracy, and response time. EEG, for example, offers excellent temporal resolution but lower spatial resolution compared to fNIRS. Response time is particularly critical for real-time applications such as neurofeedback and BCI development. Reliability is another concern, as noise and external interference can compromise data quality and reduce the effectiveness of the methods. EEG measures electrical activity from the cerebral cortex, but signal distortions occur as electrical potentials pass through the skull and scalp. These signals range from approximately -90 mV at rest to 40 mV at the peak of an action potential and require amplification, an essential step that can also introduce additional noise.

Noise sources include improper electrode placement, oxidized or deteriorated electrodes, weak scalp attachment, poor contact due to dry or oily skin, hair strands, dirt, and crusts. Additional sources include movement artifacts from muscle activity, blinking, heartbeats, and electromagnetic interference caused by electrical transients, radio frequencies, and grounding issues. Given these challenges, EEG devices require meticulous electronic design, careful assembly, and circuits for attenuating oscillating electromagnetic frequencies. Connections and circuits must be shielded, cables should be short and shielded, and electrodes must be firmly and consistently attached to the scalp. Even with these precautions, significant computational effort is needed to filter the resulting signals effectively.

Due to the complex, non-stationary, and nonlinear characteristics of EEG signals, several systems have been developed for data analysis. Signal complexity can be reduced using fast algorithms, enabling machine learning methods to automatically classify certain mental disorders with high accuracy. Disorders such as depression and epilepsy could be diagnosed at the same time. However, EEG-based diagnosis has limitations: patients may not exhibit abnormal patterns consistently, and short EEG recordings can miss critical events, leading to inaccurate results. While long-term monitoring improves the detection of abnormalities, EEG signals are highly susceptible to external interference, and detecting periods of inactivity remains challenging [27].

Usability and ergonomics are key factors that influence the adoption of these technologies. Sensors and devices can be uncomfortable during extended acquisition sessions, while complex interfaces and advanced technical requirements may limit their use in clinical or home environments. The portability of certain devices, such as brain imaging systems (fMRI or PET), is also constrained by their size and dependence on specialized infrastructure, restricting their application to research centers or hospitals. Additionally, the high cost of advanced technologies constitutes a barrier to their widespread implementation.

The fNIRS faces challenges in distinguishing brain hemodynamic changes from artifacts caused by scalp hemodynamics or movement. Photons detected by infrared receivers are influenced by physiological factors like respiration and heart rate, reducing contrast and spatial resolution. The technique also suffers from low temporal resolution and SNR [28]. Efforts to improve signal quality range from averaging multiple readings to using advanced statistical models, but low sensitivity to deeper brain layers and the inherent statistical properties of the signal complicate data interpretation [29].

Some technologies are unsuitable for patients with metal implants or cognitive impairments. Combining these tools with conventional therapeutic approaches can be complex, particularly when determining the clinical relevance of the data collected. Ethical and privacy concerns related to brain and physiological data collection further complicate their adoption, necessitating stringent regulations to ensure user trust and safety.

The EEG technology has advanced with the development of wireless systems, dry electrodes, and AI-driven data processing. Dry electrodes enhance usability by enabling faster and more accessible setups. While fNIRS is less affected by electromagnetic interference, its sensitivity is limited by the slower hemodynamic response compared to the rapid transmission of electrical signals in EEG. AI-enhanced multimodal fNIRS systems are approaching clinical-grade performance, although high costs remain a significant barrier.

The term research-grade quality is often used to describe devices suitable for scientific studies but not meeting the stringent standards required for clinical use. In contrast, low-cost EEG modules, priced under fifty dollars, offer affordable alternatives. Commonly sold as do-it-yourself (DIY) kits, these modules allow for customized assembly, making EEG technology more accessible. While they lack the advanced features and precision of clinical-grade systems, they still provide meaningful insights into brain activity.

Software is often sold separately, significantly increasing overall costs. Commercial solutions typically start around \$1,000, with advanced versions reaching up to \$8,000. Temporary licenses, renewable subscriptions, and lite versions with limited functionality are common, while open-source platforms offer more accessible alternatives. Some systems are specifically designed for neurofeedback, with software tailored to training games. Increasingly, brain monitoring devices integrate artificial intelligence (AI) for real-time data processing, anomaly detection, and rapid diagnostics. Open access to raw or AI-processed data fosters innovation and supports new research applications. Free access to AI-filtered data is a valuable resource for the neuroscience community.

Several brain equipment manufacturers offer either complete systems or modular components, allowing for user customization, though often without clear guidance for selection. Some companies, traditionally focused on wired systems, have introduced wireless options, typically limited to amplifiers without caps. Others operate exclusively through rental or contracted services, while certain technologies remain under development. Identified manufacturers include Compumedics Neuroscan (AUS), fNIR Devices (USA), Hitachi (JPN), Neurosoft (RUS), BioSemi (NLD), iCelera (BRA), Contec (CHN), Meditron (BRA), Neurovirtual (USA), TechEn (USA), Imec (BEL), Kernel (USA), Mindfield (DEU), NeuroPro (CHE), Gowerlabs (ENG), Neurotec (BRA), and Deymed (CZE). Additionally, low-cost module providers include Deuteron (ISR) and Sichiray (CHN). In some cases, websites are outdated or provide little evidence of ongoing product availability, raising concerns about whether some manufacturers are still active.

Conclusion

This review provides a comprehensive and technically grounded synthesis of the current landscape of noninvasive brain monitoring technologies, with emphasis on their applicability to neuroscience and neurorehabilitation. By systematically mapping the specifications, architectures, and operational features of commercially available EEG and fNIRS systems, the study translates complex engineering data into an actionable framework for device selection and experimental design. The proposed framework supports researchers and clinicians in aligning technical parameters with the specific goals of their investigations, facilitating evidence-based, reproducible, and methodologically sound use of neurotechnological tools.

The analysis highlights that device selection should be guided primarily by the intended research or clinical objective. High temporal resolution and signal fidelity are essential for applications such as event-related potentials and functional connectivity analysis, whereas mobility, ease of deployment, and rapid setup are critical for field studies, BCI applications, and rehabilitation in movement-rich contexts. Multimodal configurations, such as integrated EEG–fNIRS systems, further expand the potential for real-time monitoring, neurofeedback, and closed-loop virtual reality paradigms. Across modalities, core decision parameters include electrode or optode type, channel density, sampling rate, bit resolution, wireless transmission protocol, and data accessibility through standardized interfaces or SDKs.

Practical trade-offs also emerge among systems. Wet and gel-based electrodes provide the highest signal quality but require time-intensive preparation, while dry and semi-dry electrodes enhance usability and participant comfort at the cost of slightly increased impedance. Channel configurations between 8 and 32 are suitable for most BCI and connectivity studies, whereas high-density arrays ($\ge$ 64 channels) enable source localization and advanced spatial analysis. Sampling rates between 250 and 500 Hz meet the majority of experimental demands, while higher rates (\SI{\ge 1}{\kilo\hertz}) and 24-bit resolution are recommended for precision time-locked paradigms. Reliable wireless connectivity—preferably low-latency Wi-Fi for data-intensive applications and Bluetooth Low Energy for mobile protocols—supports robust multimodal synchronization and integration with immersive environments.

In applied neurorehabilitation, integration with virtual reality systems requires ergonomically optimized, low-latency devices capable of sustaining high-quality signal acquisition during motion. Systems equipped with open SDKs and native synchronization libraries facilitate seamless communication with VR engines, enabling adaptive neurofeedback and ecological data capture. Dry electrode designs are particularly advantageous in these contexts, improving participant comfort and reducing setup time while maintaining acceptable signal stability for most training and assessment scenarios.

The findings from the strong body of evidence in the scientific literature highlight a global movement toward increasing the accessibility of neuroscience research through user-friendly, affordable, and widely available devices, while also underscoring the persistent gap that remains between consumer-grade and research-grade technologies.

The compiled dataset provides an evidence-based framework to guide neuroscientists, engineers, and clinicians in selecting the most appropriate device for their specific research needs. This work also identifies critical technological trends, such as the strong convergence toward wireless architectures and the growing emphasis on open data interfaces.

Overall, this study contributes a reproducible, evidence-based technical mapping of EEG and fNIRS technologies, consolidating information from scientific, industrial, and patent sources into a unified classification framework. Beyond informing device acquisition, these findings promote greater interoperability, transparency, and standardization within the neurotechnology ecosystem. Future research should expand the evaluation scope to include longitudinal data quality, real-world reliability, and user experience metrics, strengthening the translational bridge between engineering innovation and clinical neurorehabilitation. By doing so, the field moves closer to developing adaptive, accessible, and scientifically validated neurotechnological platforms capable of transforming both neuroscience research and patient care.

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