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AN APPRAISAL OF THE NONINVASIVE ELECTROENCEPHALOGRAPHY PRODUCTION AND MARKETING

GHUFRAN M. FAHAD*, MANAF K. HUSSEIN, RIYADH A. ABBAS

Department of Electrical Engineering, College of Engineering, University of Wasit, Wasit, Iraq
*Corresponding Author: gfahid@uowasit.edu.iq

Abstract

The development of wearable system technologies has increasingly expanded towards clinical and non-clinical applications, reflecting the growing integration of scientific advancements into daily life. Electroencephalography (EEG) is a noninvasive method that records electrical activity on the scalp, generated by neurons firing in the brain. It is one of the most significant methods for monitoring brain function and diagnosing brain disorders. It enables efficient recording and analysis of brain activity signals with high accuracy. After conducting related research, there is a relative rarity of inclusive reviews of the noninvasive EEG acquisition technology. This paper provides a noninvasive EEG acquisition circuit, focusing on its core components and advanced principles underlying the devices. Various types of electrodes, preprocessing circuits, and processing circuits are discussed, with their performance and efficiency outlined. A comparative quantitative study shows differences among systems such as the ADC1299, Emotiv EPOC X, and OpenBCI Cyton in sampling rates of 128-2048 Hz, number of channels of 4-32, and input noise levels of 0.204-6.50 V_{rms}, highlighting trade-offs between accuracy and portability. Furthermore, the study highlights potential advancements in Brain-Computer Interfaces, Neuroscience Research, Neuromarketing, Biometrics, and Custom Solutions. The ongoing development of EEG signal analysis is expected to expand its applications across diverse fields.

Keywords: Brain-computer interfaces (BCI), Brain monitoring, Electroencephalography, Neuroscience, Signal processing.

1. Introduction

The brain constitutes the most sophisticated neurological system; the human brainwave signal produces unparalleled levels of neuronal activity that manage all bodily functions. In 1924, Hans Berger first utilized scalp electrodes to capture electrical activity in the human brain. An Electroencephalogram measures brain activity in physiological processes of neural activity that reflect a bioelectric signal [1]. In contemporary neuroscience research, increasingly popular applications of EEG acquisition devices are being used to control intelligent devices [2, 3].

The most common classification methods for EEG recording equipment include device type, type of electrode, and application domain, as seen in Fig. 1. Categorized by device type, it comprises wired and wireless EEG device communications. Wired EEG headsets require cable connections between recording systems and transfer data from electrodes and amplifiers to a computer during a given time. Still, the movement in recording EEG signals can cause artifacts in the wireless connection [4]. Wireless EEG devices utilize wireless or Bluetooth transmission technology without wired connections and offer more flexibility [5].

One of the essential drawbacks is that, through the recording of the brain data, wireless EEG headsets may experience a loss of wireless communication and failure to collect the data. The types of electrodes include invasive and noninvasive electrodes. Noninvasive electrodes capture brain data from the brain over the scalp without surgical intervention, making them safer and thus having broader applications. Typically, invasive electrodes provide high accuracy with more spatial resolution and ensure surgical intervention, making them riskier [6, 7]. Recently, the domain applications of the device have an application of the devices have moved to clinical-grade and consumer EEG devices.

Consumer-grade devices feature more channels, increased sampling rates, and higher precision, which are utilized for scientific investigations. Clinical EEG devices are used for clinical metrics and conform to medical monitoring, treatment, and diagnosis [4]. EEG acquisition devices can transform brainwave signals into command signals, which can be explained during computer or external control devices [8]; this enables human and machine interaction to enhance the efficient integration of tasks during daily life.

In recent years, the increased popularity of EEG acquisition system applications and research has been due to the development of computer technology, neuroscience, and the enhancement of signal processing [9]. Continuous advances in EEG acquisition systems, the field of applications, and research on the devices. That has become deeper and more specialized.

Hence, this paper introduces an overview of the development of noninvasive EEG technology, focuses on EEG signal acquisition and signal processing, and discusses the present challenges and technology bottlenecks in noninvasive EEG systems. Finally, this paper provides domain applications of noninvasive EEG technology. Furthermore, it will be followed by a conclusion for future trends in developing noninvasive EEG technology.

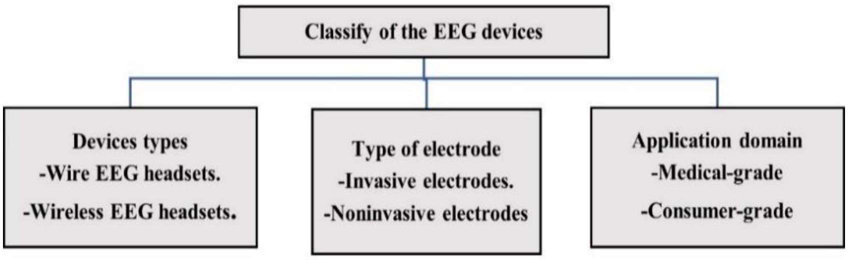

Fig. 1. Classify EEG devices based on the equipment recorded.

2. Review Method

This article introduces a comprehensive review of an appraisal of noninvasive EEG signal acquisition. The methodology is intended to provide a deep comprehension of the essential components and advanced fundamentals underlying these systems. This review depends on studies and publications between 2015 and 2024, which achieve thorough coverage, select the structure of the publications from esteemed platforms, which include Web of Science (https://www.webofscience.com), arXiv (https://arxiv.org/), IEEE Xplore (https://ieeexplore.ieee.org), and PubMed (https://pubmed.ncbi.nlm.nih.gov/).

The methodology comprises 45 papers that were analysed utilizing topical assembly, and that present a detailed analysis of the field, which covers the Components of the EEG Signal Acquisition System, Classification of EEG Devices, and Applications, as it provides the Challenges and Future Outlooks.

In summary, the systematic approach is based on compiling and analysing data from related academic sources to offer a comprehensive and specific overview of noninvasive EEG data acquisition approaches and their different application field.

3. EEG Signal Acquisition

Typically, EEG acquisition system components include electrodes for data recording and a preprocessing circuit that can remove noise and artificial signals, as classified in Fig. 2, while extraction and selection of the feature have been in processing circuits and the host computer [10, 11]. The technology is used in various applications, such as the medical field, mobility assistance, and intelligent systems. Some applications require sending the classification results to the controlling devices [12].

The EEG acquisition system must provide accurate results and minimal noise in measurements, assuring user comfort and security [13]. Every component is essential and critical to the system [10, 11].

3.1. EEG electrodes

In psychology, neuroscience, and different research applications, the first component of EEG signal acquisition employs sensors or electrodes for the human scalp without any surgical intervention [13]. Noninvasive EEG electrodes are placed over the scalp to capture EEG signals and convert ionic physiological signals to electrical signals. Electrode placement adheres to internationally agreed rules, generally classified into (10-10) or (10-20) [14]. As illustrated in Fig. 3, these numbers denote the distance from one electrode to another, while the features associated with the electrode-tissue interface may limit system performance [15].

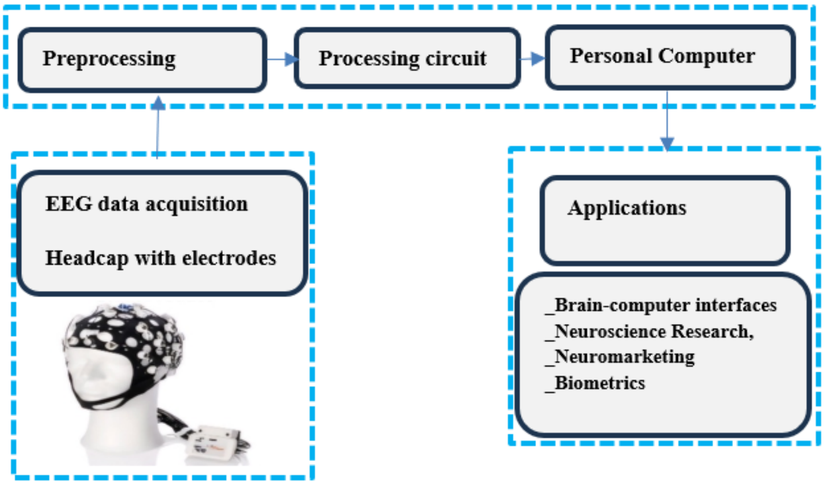

Fig. 2. EEG signal acquisition.

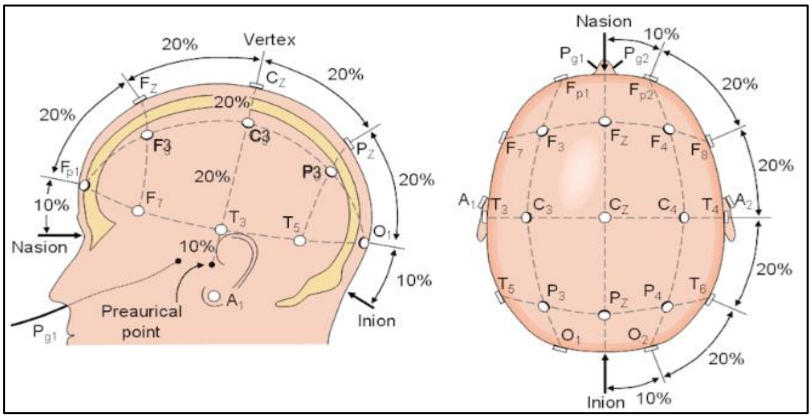

Fig. 3. International 10-20 system (Reaves et al. [14]).

Wearable surface electrodes can be categorized into several categories, such as mental-plate electrodes (long ranged use), disposable foam pad electrodes (effectively cost), metallic suction electrodes (strapless), floating electrodes (reduce motion artifact), and flexible electrodes (enhanced comfort) .flexible metal or polymer electrode with pins that slide into hair, it is predominant from factor for high guilty contact in wearable EEG measurements [16].

The materials of an electrode, which are heavily dependent on their applications and include Gold, Platinum, Silver chloride (AgCl), and sintered Silver/silver chloride Ag/AgCl electrodes, are considered among the most often utilized EEG electrodes according to their regular data quality, improved signal-to-noise ratio, dependability, and economic viability [17]. Gold and platinum electric electrodes are expensive yet strong and straightforward to repair since gold electrodes offer enhanced signal quality at frequencies exceeding 0.1 Hz [16].

Hence, electrode impedance depends heavily on the electrode's materials. As illustrated in Fig. 4, noninvasive EEG electrodes generally can be categorized as wet and semidry electrodes (electrolyte contact), dry noncontact or contact electrodes, based on contacts between the body's epidermis and the electrode [17]. Dry electrodes contact the scalp directly without using gel or paste. Different electrode types (e.g., needles, pins, and spiders) and materials have been introduced for both dry and semidry electrodes. Dry electrodes have several advantages over paste or gel electrodes [18].

The preparation and cleaning durations are much shorter, especially for many channels [19]. Nevertheless, dropout rates for dry electrode recordings are higher, and they are more prone to artifacts from movements [18]. However, sintered Ag/AgCl electrodes demand the conductive gel, and the usage and preparation methods are complex and consume time [16].

Consequently, there has been an increase in the variety of EEG electrodes to satisfy the distinct needs of various application domains [20]. These electrodes became available as solutions for reducing the issues raised by Ag/AgCl electrodes while satisfying particular research requirements [17]. To enhance the structure and further illustrate, Table 1 introduces the related literature on EEG electrodes.

Table 1. Summary of literature on EEG electrodes.

Reference	Technique	Main contribution
Namazi et al. [13]	Noninvasive electrode	The first element of EEG data acquisition involves using electrodes without any surgical intervention.
Reaves et al. [14]	10-20 international system	Committed to a (10- 20) international system for select electrode location and distance between these electrodes
Ball et al. [15]	Electrode tissue contact	Features related to the electrode-skin interface can affect system performance.
Xu et al. [16]	Types of electrodes	Introduces polymer electrodes with pins for high-quality contact, the gold electrodes offer good signal quality, and the Ag/AgCl electrodes require conductive gel, which is time-consuming to apply and has complex preparation modes.
Liu et al. [17]	Electrode materials	Identifies the further used EEG electrode concerning signal quality, improves signal-to-noise ratio, and pricing. It classifies noninvasive electrodes according to the contact of the electrode with the skin. Notes the availability of solutions for minimizing problems raised by Ag/AgCl electrodes
Fiedler et al. [18]	Dry electrodes	Reflects dry electrode dropout rate data and more exposure to artifacts by recording
Fiedler et al. [19]	Dry electrodes	Introduces dry electrodes that require less time for preparation and cleaning, especially when applying many channels
Jin et al. [20]	A variety of electrodes	Refers to the improving diversity of electrodes manufactured to satisfy the specific requirements of various application fields.

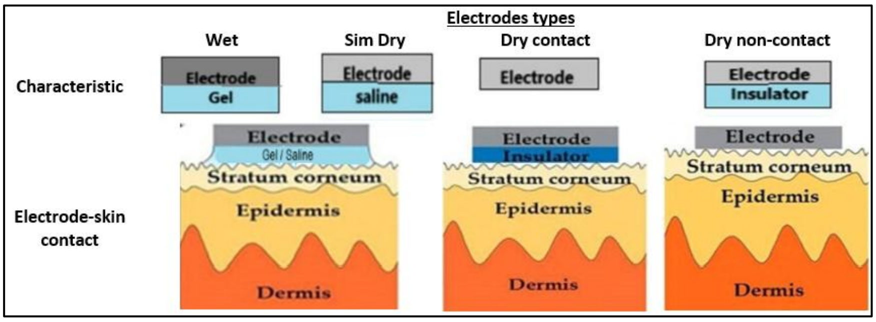

Fig. 4. Types of electrodes contact with the body.

3.2. The preprocessing circuits

The preprocessing circuit is crucial in acquiring EEG signals; it ensures an optimal density of the channels, low noise, and increased accuracy in the recorded data [10]. During the capture, EEG signals interfered with various noises and artifacts, which are existing challenges for signal processing and analysing the signal [1, 8]. Hence, before EEG signal recording, typically, this circuit comprises essential modules involving amplifiers, ADC, filters, and electrodes of the reference, ensuring enhanced signal quality and accuracy.

Several main modules involve amplifiers, ADC, filters, and reference electrodes, providing enhanced signal efficiency and accuracy. Amplifiers increase the amplitude of weak EEG signals, improving their processing [16]. The type of filters utilized removes noise and some artifacts from data while maintaining the primary frequency components of EEG signals [21]. Within EEG signal acquisition, an Analog-to-Digital Converter (ADC) is the fundamental component that transforms voltage signals from analogue to digital format, improving data recording accuracy and clarity [22].

The sampling rate for ADC dictates the quantity of data points collected per second [23]. It must be chosen for various EEG investigations to meet the experimental conditions, and appropriate parameters must be selected, such as a higher resolution, lower power consumption, and a small-sized ADC, which is more suitable for portable and wearable devices. Therefore, it is essential to utilize low-noise ADCs and integrate noise reduction methodologies, such as differential results and filtering, during the design process to enhance data quality [23, 24]. The influence of the noise of the power supply should also be considered for the ADC [25].

Due to the sensitivity of ADCs to power-supply noise, it is essential to utilize a stable power supply to reduce their impact on signals. Additionally, it is crucial to consider the choice and placement of the electrodes of reference to minimize the noise induced by the power supply [23]. Reference electrodes are usually positioned in designated placements on the human scalp, distanced from the principal origins of the brain's electrical activity. It is regarded as zero or a defined value, enabling the calculation of potential differences at other electrodes [21].

Thus, they required efficient analogue front ends and high-precision analogue-to-digital converters (ADCs). There are essential factors that must be considered to achieve high complementarity and good performance, including ADC resolution, sampling rate, power supply noise, reference electrodes, power consumption, and dimensions that should be considered [23]. Various EEG investigations might require unique preprocessing circuits to meet practical experimental demands. For example, Wang et al. [26] developed an amplification circuit for analogue voltage for essential applicability. Table 2 reflects contributions to the design of preprocessing circuits.

Table 2. Summary of literature on the preprocessing circuits.

Reference	Technology	Actual contribution
Uktveris and Jusas [10]	Preprocessing circuit design	Focus on the fundamental role of the preprocessing circuit in EEG recording signals and increasing the accuracy of these data. Also, states that every component in the acquisition system is essential.
Suhaimi et al. [1] and Chiesi et al. [8]	Noise and artificial removal, ADC, and preprocessing circuits	Identifies noise and artifacts that interfere with EEG data recording, posing existing challenges for signal processing. Also, states that ADCs and preprocessing circuits are essential for enhancing the accuracy of the signal, denoising, and removing artifacts.
Xu et al. [16]	Amplifiers	Explains how to improve data processing by using an amplifier, which applies to increasing the amplitude of weak EEG signals.
Kumar Sahu and Kumar Sahu [21]	Filters and reference electrodes	Explains the essential function of filters in removing noise and some artifacts from data while stating the essential raw EEG data. Describes how reference electrodes enable the calculation of potential differences at other electrodes.
Martins et al. [22]	ADCs	Knows the Analog to Digital converter as an essential component in signal acquisition for clarity and resolution of the data recording
Yi et al. [23]	ADCs and reference electrodes	The considerations for ADC selection are more suitable for portable and wearable devices. Emphasizes the importance of choosing the location of reference electrodes to minimize noise resulting from the power supply.
Tang et al. [24]	Filters	Supports the use of filters in noise reduction methodology by the manufacturing process to improve signal quality.
Zhou et al. [25]	Power supply noise reduction	It should be considered that the influence of power supply noise affects the sensitivity of the ADC.
Wang et al. [26]	Amplification and low-pass filter	Developed an amplification circuit for analogue voltage utilizing an INA128 and TL084. Also, using a low-pass filter to reduce aliasing in EEG data is recorded.
Acharya et al. [27]	ADC1299	Provides ADS1299 and properties for use in the preprocessing circuit

The device utilized an instrumentation amplifier (INA128) as the preamplifier, amplifying EEG signals by a factor of 1000 times while having high input impedance and Common Mode Rejection Ratio. Additionally, the post-amplifier employed the TL084 with a Zero-Offset Circuit to calibrate a range of weak signals from 0 to 5 V. They employed a low-pass filter to mitigate aliasing in EEG signals.

Furthermore, Acharya et al. [27] reviewed an ADS1299 development board produced by Texas Instruments. The research presented suggestions for the ADS for EEG acquisition because of its low power consumption, little input reference noise, and 0.204 - 6.50 V_{rms}, and superior overall performance compared to other devices in the same category.

In conclusion, analogue-to-digital converters (ADCs) and preprocessing circuits play an essential role in EEG signal acquisition, enhancing signal clarity and accuracy and reducing interference from noise and artifacts [1]. The circuit design must be flexible to particular requirements to accommodate the varied needs of various EEG experiments.

3.3. Processor circuit

In EEG signal acquisition, processing circuits enable the instantaneous processing of raw data signals, ensuring low power consumption and high accuracy. In the literature, choosing the processor circuit for interfacing with the processing circuit depends on the field application and the required computational performance [28, 29]. Currently, the most commonly applied are field-programmable gate arrays (FPGAs) [30], STM32 microcontrollers [31], and Raspberry Pi [2].

FPGAs are widely used in real-time EEG signal processing due to their parallel processing capabilities and low latency. Also, it is reconfigurable and can implement advanced signal-processing algorithms dealing with Real-time artifact removal and feature extraction [30]. FPGA processing circuit. It prefers high-density EEG data streams efficiently for applications like brain-computer interfaces (BCIs) and seizure detection [29]. Table 3 outlines the specific processing based on some parameters that trade off with EEG systems.

Table 3. Some parameters for the most common processing circuit.

Processor	Real-time performance	Power consumption	Cost	Latency	Flexibility
FPGA	High	Moderate	High	Low	Real-time, multi-channel EEG processing
STM32 microcontrollers	Moderate	Low	Low	Moderate	Portable/wearable EEG systems
Raspberry Pi	Moderate	High	Low	Moderate	Educational projects, low-cost EEG systems

Meanwhile, a digital signal processing (DSP) circuit is a specific design utilized for digital signal processing, often in implementing signal processing using algorithms, which include digital filtering and fast Fourier transforms [32]. Typically, STM32 microcontrollers include ADCs, timers, communication interfaces, and low power consumption, and they are suitable for portable and wearable EEG systems [31, 33]. Traditional processor circuits, such as the central processing unit (CPU), can be applied to EEG signals.

Typically, CPUs are used to process the data and implement complex algorithms like neural networks and machine learning [34]. However, in most popular graphical user interfaces (GUIs) and medical diagnoses like sleep monitoring and neural signal analysis, Raspberry Pi offers real-time signal processing and high-density data recording because it can be used in EEG systems [35].

In Conclusion, for EEG signal acquisition, the choice of a processor is based on the specific requirements of the EEG acquisition and the development of more efficient and accurate EEG systems, such as real-time performance, power efficiency, stability, and cost. Table 4 provides a comprehensive overview of processing circuits through various EEG acquisition systems.

Table 4. Summary of the literature on the processing circuit.

Reference	Technique discussion	Main contribution
Pinho et al. [28] and Belwafi et al. [29]	Processor circuit	Emphasize the selection of the processor circuit for interfacing with consideration of the design of devices and using the device's domain.
Qin et al. [30]	FPGAs	Offers that FPGAs are preferred and widely utilized in real-time EEG signal processing. Additionally, they can implement advanced algorithms for reducing noise and artifacts.
Kancaoğlu and Kuntalp [31] and Vaithianathan et al. [33]	STM32 microcontrollers	Describes the considerable STM32 microcontrollers that are suitable for wearable EEG devices
Rai and Deshpande [2] and Benomar et al. [35]	Raspberry Pi	Introduces Raspberry Pi's potential as one of the most commonly employed processor circuits for EEG. It can be utilized in graphical user interfaces and sleep monitoring.
Kwiatkowski [32]	DSP	Shows that a DSP processing circuit is manufactured explicitly for digital data processing, mostly implementing signal processing algorithms such as digital filtering and FFT
Moroz et al. [34]	CPU	Identifies that can be implemented, complicated algorithms based on the CPU for EEG data processing

3.4. Comparative analysis of EEG acquisition techniques

This presented paper refers to a significant development in EEG signal acquisition systems, with a focus on noninvasive EEG wearable systems. Table 5 introduces a comparison of some commercially available systems and devices in the market. Based on the defined parameters, such as:

Presently, EEG devices, especially the noninvasive EEG wearable ones, show notable advancements. These are apparent in the system to record and analysed EEG signals with high accuracy and reduce noise and artifacts, due to the advancement in the efficient processing circuit, including amplifiers, ADC, and filters. Wireless systems provide improved flexibility and ease of preparation, supporting portability. The large variety of types of electrodes (dry, wet, and Hybrid) frequently employs materials such as Ag/AgCl for good signal quality.

Utilizing robust processing units such as FPGAs enables high accuracy and efficient processing of vast amounts of data in real time.

Furthermore, the existence of inexpensive devices, which sometimes offer performance comparable to medical-grade devices, has expanded accessibility for commercial applications. Despite that, wired EEG devices are exposed to data distortion or loss due to the user's movement. At the same time, wireless devices may experience disconnection while recording the signals. Although simple to prepare, dry electrodes are more prone to noise and artifact interaction. However, wet electrodes require time-consuming preparation. Also, the sensitivity of ADCs requires a stable power supply and accurate location of reference electrodes to ensure signal quality.

Additionally, the medical-grade systems are density-channel and highly costly, sometimes costing tens of thousands of euros. In addition to the qualitative comparison, quantitative analysis across several EEG systems reveals significant variations in technical performance. For instance, the Emotiv EPOC X provides a sampling rate of 256 Hz with 14 wet electrodes, achieving high portability and moderate signal quality suitable for non-clinical research.

In contrast, the g.tec Unicorn Hybrid Black operates at 250 Hz and supports hybrid (dry/wet) flexible electrodes, offering improved comfort and reduced setup time. Meanwhile, the ANT Neuro eego mini 24 reaches a sampling rate of up to 2048 Hz, emphasizing medical-grade accuracy but at a higher cost and complexity. These quantitative indicators emphasize the trade-off between signal quality, portability, and usability, which are crucial for selecting the appropriate EEG system for specific research or clinical applications.

4. Key Findings and Research Gaps in EEG Systems

This review provides the gaps in past studies that have not been resolved in research, and an adequate analysis can be specified as follows:

- Minimal of the research that covers comprehensive reviews on the field: This demonstrated a gap in the literature, which the study itself addresses by introducing a comparison of noninvasive EEG Acquisition systems.
- Current technological challenges and bottlenecks: although advancements in noninvasive EEG systems have been made, there are existing challenges and system bottlenecks in the area. The paper focuses on requiring challenges, which include the need to improve electrode manufacture, optimize signal processing, and choose a Microprocessor. These challenges refer to a field that needs more research and advancement.
- Rare research in Biometrics and Neuromarketing application, which appears when compared to other fields such as BCI and neuroscience research. Further study is required.

Table 5. Comparative analysis of EEG devices.

Devices/ system	Production Company	Year	Number and type of electrode	Processing circuit	Sampling rate (Hz)	Prices (k€)	Properties
EPOC X	Emotiv		14 electrodes & wet (Fixed)	Digital converter (ADC) and filters.	128/256	<1	No Medical certification
INSIGHT	Emotiv		5 electrodes & dry (Fixed)	Amplifiers, ADC, and filters.	128	<0.5	No Medical certification and a comfortable design
MUSE2	InteraXon	2028	4 electrodes & dry (Fixed)	Amplifiers, ADC, and filters.	256	<0.5	No medical certification
Unicorn Hybrid Black	g-tec	2019	8 electrodes& Hybrid (dry/wet)/ flexible	Amplifier, ADC, and filters.	250	<1	No medical certification
Cyton+ Daisy	Open BCI	2014	16/8 electrodes & Hybrid (wet/dry/Gel)/ Flexible	Amplifier, ADC, and filters. Processors (STM32 or FPGAs)	250/125	1-2	Open-source hardware configuration is available as 3D printable models
Stat X-series X-24	Advanced Brain Monitoring	2020	20 electrodes & Gel (fixed)	High-precision amplifiers, ADC, and filters	256	12-15	Only use in medical certification
Eego mini24	ANT Neuro	2022	20 electrodes & Gel (Fixed)	High-accuracy amplifier, ADC, and filters.	2048	-	Medical certification and a very high sample rate
Mobile	CGX (Congnionics)	2021	128/72 electrodes & Gel (Flexible)	High-accuracy amplifier, ADC, and filters	500	45-60	No medical certification, density-channel, and high cost

5. Recommendations and Proposed Solutions

To improve the future advancement of noninvasive EEG systems and the processing of current bottlenecks in technologies.

- Focusing on practicalized comprehensive research on noninvasive EEG acquisition technology: this paper partially processes the defined rarity of the topic, but requires further focus for future review, such as comparative analysis of special electrode types, advancement of EEG signal processing theories, or practical application.
- Deep into the development of electrode manufacture, such as improving dry electrodes to minimize artifacts, featuring the flexible and Hybrid (dry, wet, and gel) electrodes.
- Develop a signal processing circuit and a Microprocessor that includes a focus on the signal processing algorithms and improving the performance of preprocessing circuits.
- Development processing circuit: that introduces Field-Programmable Gate Array (FPGAs) and continues to the microcontroller and embedded processors such as STM32 for reduced power supply, and Raspberry Pi, which is commonly used.
- Expand studies in an undiscovered application field: increasing research in biometrics and neuromarketing research, the latter field focuses on measuring expectations, practical results, and explaining consumer favourites. Presently, that is enhancing the value and importance of research.

6. EEG Devices Available in the Market

To succeed in the experiment, choose the EEG devices carefully. When researching the prices of EEG headsets available in the market, the placement of EEG electrodes may vary slightly from the typical 10-20 International System, based on the headset's architectural design. Historically, noninvasive electrodes were positioned on the scalp; however, technological advancements have enabled the measurement of electrical activity, Yazdani et al. [36].

EEG devices can include a medical-grade device and a wearable, low-cost EEG device. Medical-grade EEG devices typically provide 16 to 32 channels within a headset, depending on the manufacturer. They have an advantage relative to alternative techniques and involve reduced hardware expenses compared to Magnetoencephalography. The accessible, Low-Cost, Consumer-grade wearable EEG headset would feature 2 to 14 channels [37], and using an affordable one offers comfort. It simplifies the process of positioning the device on the user's head, which is essential for researchers and users.

Interestingly, the affordable wearable EEG headset with fewer electrodes demonstrated comparable performance to medical-grade EEG headsets when utilized by a user [1]. Nevertheless, these inexpensive EEG headsets often feature electrodes located at the frontal lobe. EEG headsets use more channels to incorporate electrodes in the parietal, temporal, and occipital lobes, as apparent by the 14-channel Emotiv EPOC+ and Ultra cortex MarkIV [38], as seen in Table 6.

Describe the pricing for the current market and available features for EEG headsets. Systems are sorted by price (k€) as of December 2022. Characteristics displayed include device, company, industry year, and number of electrodes. Electrode Placement (fixed or just flexible), Reference Location (E: Earlobe, M: Mastoid, 2M: Linked Mastoids, Flex: Multiple Reference options, otherwise 10-20 system), electrode connection type (i.e., wet, dry, gel; hybrid indicates that the same electrodes can be utilized in various configurations), Sampling Rate (HZ), Medical Certification. a hyphen (-) signifies that the information was unattainable.

These possess wireless data conversion capabilities, eliminating unnecessary cables and improving portability and ease of setup. Moreover, companies like Open BCI offer 3D printable models and hardware configurations for the EEG headset, enabling limitless modification of headset designs.

In recent years, the accessibility of these technologies has markedly enhanced [39], and the use of the application domain of EEG devices, including research-grade and clinical-grade EEG devices, has increased [30].

7. EEG Applications

EEG devices can provide significant insights into the interaction between people and machines, imagination, cognitive disabilities, and mental health issues. Consequently, scholars across various fields of study have employed it. The major categories of EEG data applications are brain-computer interfaces (BCI), neuroscience research, neuromarketing or consumer neuroscience, biometrics, custom solutions, and neurofeedback (Neurotherapy). Table 7 illustrates the EEG signal applications and the EEG devices applied in each field.

- Brain-computer interfaces (BCIs) often include the Brain-Machine-Interfaces (BMIs)and are a prevalent application of EEG services. They utilize real-time data to operate and manage electronic and mechanical systems [40, 41]. BCI devices serve as a Human-Machine Interface to assist those minds experiencing motor difficulties, ensuring those unable to communicate with others [42]. BCI systems intended for individuals with disabilities do not depend on muscular motions; they utilize distinct brain activity, such as envisioning an action, and convert it through control functions and others [41]. Typical applications of brain-computer interfaces (BCIs) encompass autonomous navigation using digital or mechatronic devices, assistance for individuals with disabilities or motor impairments, and neurogaming and entertainment.
- Neuroscience Research Neuroscience allowed clinical and non-clinical researchers. It understands the nervous system's functionality and how the brain acts in different mental issues and emotional states for human experience [4]. Researchers used EEG equipment in the following studies, such as cognitive neuroscience, Behavioural Neuroscience, and Neurophysiology. By presenting various media, neuroscience can describe human emotion in virtual reality, irrespective of tactile interaction with the environment [43].

Table 6. EEG available devices in the market and their specifications.

Device	Company	Production year	No. of the electrode	Electrode placement	Reference locations	Electrode connected type	Sample rate (Hz)	Medical certification	Pricing information (k€)
EPOCX	Emotiv	-	14.	Fixed	P3/P4/M	Wet.	256/128	No	<1
EPOC-FLEX	Emotiv	-	32.	Fixed.	Flex/E	Wet. Gel.	128	No	1-2
INSIGHT	Emotiv	-	5	Fixed	M	Dry	128	No	<0.5
Unicorn Hybrid Black	g-tec	2019	8	Flexible	M	Dry/gel (hybrid)	250	No	<1
Unicorn Naked BCI	g-tec	-	8	Flexible	M	Dry/gel (hybrid)	250	No	<1
MUSE 2	InteraXon	2018	4	Fixed	FPz	Dry	256	No	<0.5
MUSE S	InteraXon	2021	4	Fixed	FPz	Dry	256	No	<0.5
Crown	Neurosity	2021	8	Fixed	Tz	Dry	256	No	<1
Cyton+ Daisy	Open BCI	2014	16/8.	FLEXIBLE	E.	Wet/dry gel.	250/125	No	1-2
Ganglion	Open BCI	2016	4	FLEXIBLE	E.	Dry/wet gel.	200	No	<1
B-Alert X10	Advanced Brain Monitoring	2010	9	Fixed	2M	Gel	256	No	8-10
B-Alert X.24	Advanced Brain Monitoring	2012	20	Fixed	2M	Gel	256	No	11-15
Stat X-series X.24	Advanced brain monitoring	2020	20	Fixed	2M	Gel	256	Yes	12-15
Eego mini-24	ANT Neuro	2022	24	Flexible	CPZ/CZ/M	Dry, Wet, Gel	2048	Yes	-
Eego mini-10	ANT Neuro	2016	8.	Flexible.	Cpz/Cz/M.	Dry, Wet, Gel	2048	Yes	-

Table 6 (Continue). EEG available devices in the market and their specifications.

Device	Company	Production year	No. of the electrode	Electrode placement	Reference locations	Electrode connected type	Sample rate (Hz)	Medical certification	Pricing information (k€)
Eego sports	ANT Neuro	2015	128/64/32	Flexible	CPZ/CZ/M	Dry, Wet, Gel	2048	Yes	-
Air	Bitbrain	2018	8	Fixed	E	Dry	200	No	5
Diadem	Bitbrain	2016	12	Fixed	E	Dry	200	No	13
Hero	Bitbrain	2022	9	Fixed	E	Dry	200	No	13
Neuroheadband	Bitbrain	2023	5	Fixed	E	Dry	200	Ongoing	2-4
Live Amp	Brain products	2015	64/32/16/8	Flexible	Lex	Dry, Wet, Gel	1000/500/250	No	-
X-on	Brain products	2022	7	Fixed	E	Dry, Wet, Gel	500/250/125	No	2-5
Mobile	CGX (Congnionics)	2021	128/72	Flexible	-	Gel	500	No	45-60
Quiker20r v2	CGX (Congnionics)	2021	21	Fixed	E	Dry	500	No	20
Quiker32r	CGX (Congnionics)	2021	30	Fixed	E	Dry	500	No	28
Explore	Mentalab	2020	8/4	Flexible	Flex	Dry, Gel	1000/500/250	No	4.5-6
Explore+	Mentalab	2022	32/16/8	Flexible	Flex	Dry, Gel	1000/500/250	No	7-20
DSI-24	Wearable sensing	2009	21	Fixed	PZ/E	Dry	600/300	No	-
DSI-7	Wearable sensing	2023.	7	Fixed	PZ/E	Dry	600/300	No.	-
DSI-7 Flex	Wearable sensing	2013	7	Flexible	-	Dry	600/300	No	-
VR300	Wearable sensing	2015	7	Flexible	P4/E	Dry	600/300	No	-
Zeto WR19	Zeto	2020.	21.	Fixed	CZ/M/E.	Dry	500/250	Yes.	-

- Neuromarketing or Consumer Neuroscience: Neuromarketing, also known as Consumer Neuroscience, is a recent science within the field of advertising that is focused on understanding consumer demands, behaviours, and emotions, as well as predicting their decision-making processes [44]. Neuromarketing studies intended to meet expectations concerning practical products and comprehend consumer preferences [45], and related responses to television proclamations through EEG data analysis [46].
- Biometrics: The Identification and differentiation of individuals using behavioural or psychological features, including fingerprints, voice, facial recognition, iris patterns, gait, and improved posture, is termed biometrics [47]. Research indicates that EEG data may show variations among individuals. The cognitive and emotional states of the brain have currently been employed for biometric identification, utilizing EEG data to recognize individuals [48, 49]. Biometric systems based on EEG signals have increased attention because of privacy compliance and universality. EEG-based biometric systems received increased attention because of privacy compliance, universality, and tolerance to deceiving events [50].
- Custom Solutions and Neurofeedback (Neurotherapy) are other fields of research that apply EEG devices to create a comfortable and simple environment, which can be suitable for improvement [51].

Following neuroscience, brain-computer interfaces (BCIs) have garnered the most interest from researchers regarding EEG data. In contrast, the proportion of studies in biometrics and neuromarketing is very minimal [43, 52]. Many EEG devices come with open-source software for signal processing and analysis, such as BCI2000 and OpenBCI. These tools are essential for researchers developing custom algorithms and experimental paradigms [1, 40, 41].

Table 7. Applications of EEG signals with EEG devices.

Applications	Filed	Production company	EEG headset
Brain-computer interface and Neurogaming	Autonomous Navigation Digital or Mechatronic device Serving people with a motor disability or activity impairment. Neurogamig/Entertainment.	Emotiv Advanced Brain Monitoring. Neuroelectrices. NeuroSky ANT Neuro. mBrainTrain Wearables sensing	EPOC+, EPOC-, EPOC flex, INSIGHTS. B-Alert X-Series ENOBIO. Mind Waves, Mind Waves Mobile.2 Eego my lab, EegoTM mini-series SMARTFONES, SMARTING DSI.24, DSI.7, VR.300, Neuro Cube.
Neuroscience Research	identification and distinction of individuals	Advance Brain Monitoring mBrain Train. Neuroelectric ANT neuro Wearable sensing	B-Alert. X-Series. ENOBO. Eego mylab. SMARTFONES, SMARTING DSI.24, DSI.7, DSI.7 flex, VR.300.
Neuromarketing.	environment physiological Educational research. Sport, fitness, and meditation	Advanced Brain Monitoring mBrainTrain Wearable sensing	DSI.24, DSI.7. B-Alert X-series. MARTFONE, AMARTING.

Table 7 (Continue). Applications of EEG signals with EEG devices.

Applications	Filed	Production company	EEG headset
Ergonomics and Biometrics	Understand brain functionality Neurology neurofeedback, e.g., diagnosing and predicting abnormal brain diseases and cognitive impairments	Advanced Brain Monitoring Wearable Sensing Sleep studies: OPENBCI, Advanced Brain Monitoring, music TM, EB Neuro, Brain products ANT Neuro mBrainTrain Neuroelectrics	B-Alert X-Series DSI.24, DSI.7. Sleep Studies as: EEG electrodes cap kit, sleep profiler, Muse 2, Muse S Enobio Mind Wave mobile 2 Eego, mylab SMARTFONES, SMARTING
Custom solutions, e.g., education, Sport.	Understand consumers' needs, behaviour, and emotions Forecasting consumers' decision-making process	Neuroelectrics NeuroSky ANT Neuro Wearable sensing.	Enobio Mind Wave, Mind Wave mobile 2 Eego my lab. DSI 7 Flex

8. Conclusion and Future Outlooks

Innovative technology increases the development of noninvasive EEG data collection technology, enlarging its potential and functional competence. EEG data collection systems have recently been developed to enhance efficiency, accuracy, and practicality. Furthermore, challenges that remain in the selection of the most suitable from this phase are electrode design, enhanced signal processing, and the microprocessor, which are then applied to the algorithm, which enhances classification performance depending on the specific application and task requirement, and has achieved notable success.

Future efforts could continue in various applications and other research that can promise more profound insights into the future. Nonetheless, we currently have some research about biometrics and neuro-marketing, and thus, there may be promising avenues for more studies.

Abbreviations

ADC	Analogue Digital Converter
ADC1299	Low power, low noise, 8-channel analogue front-end for biopotential measurements (Texas Instruments)
ADS	Analogue Digital Sigma-Delta
Ag/AgCl	Silver/Silver Chloride
BCI	Brain-Computer Interfaces
BMIs	Brain-Machine-Interfaces
CPU	Central Processing Unit
DSP	Digital Signal Processing
EEG	Electroencephalography
FPGA	Field-Programmable Gate Arrays

GUIs	Graphical User Interfaces
INA128	Instrumentation Amplifier
STM32	STM 32-bit Microcontroller
TL084	Texas Instruments
V_{rms}	Root Mean Square Voltage

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