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Review

Electroencephalography (EEG) Technology Applications and Available Devices

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Abstract: The electroencephalography (EEG) sensor has become a prominent sensor in the study of brain activity. Its applications extend from research studies to medical applications. This review paper explores various types of EEG sensors and their applications. This paper is for an audience that comprises engineers, scientists and clinicians who are interested in learning more about the EEG sensors, the various types, their applications and which EEG sensor would suit a specific task. The paper also lists the details of each of the sensors currently available in the market, their technical specs, battery life, and where they have been used and what their limitations are.

Keywords: EEG; EEG headset; EEG Cap

1. Introduction

An electroencephalography (EEG) sensor is an electronic device that can measure electrical signals of the brain. EEG sensors typically measure the varying electrical signals created by the activity of large groups of neurons near the surface of the brain over a period of time. They work by measuring the small fluctuations in electrical current between the skin and the sensor electrode, amplifying the electrical current, and performing any filtering, such as bandpass filtering [1].

Innovations in the field of medicine began in the early 1900s, prior to which there was little innovation due to the uncollaborative nature of the field of medicine. Innovation in diagnosis and treatment came from interdisciplinary advances in the applied sciences, such as those of physics and chemistry. One such innovation was the discovery of the small electrical currents produced by the brain and other organs. Measurement of electrical activity, such as in EEG, was not performed until after 1903, when the technique to measure the electrical activity of the heart was discovered by Willem Einthoven. This measurement technique was extended to the brain to extract the EEG signal [2].

2. EEG Device Design Technology

2.1. Connection Types

2.1.1. Wired and Wireless Communications

Wired and wireless EEG headsets transfer the data to a computer via a cable, wireless or Bluetooth connection, respectively. Wired EEG connections are more stable and often can transfer more data in a given time, but do not offer the freedom of movement provided by wireless connections. One of the main drawbacks of wireless EEG headsets is that, during the capture of brain data, the headset may lose its wireless connectivity and not record the data. Regardless of the connection type, the movement of cables and electrodes can cause artifacts in the EEG signal, as it can disrupt the connections between the electrodes and the scalp.

2.1.2. Electrode Connection

EEG devices require a consistent electrical connection between the individual electrodes and the scalp of the individual wearing the device. This can be achieved in a variety of ways, some of which are listed below.

2.1.3. Wet EEG Devices

There are different types of wet EEG devices discussed below (Figure 1).

(**a**) (**b**) (**c**)

Figure 1. (**a**) dry, (**b**) saline solution, (**c**) gel-based.

Soft gel-based: Using this connection, electrodes connect with the scalp by applying conductive gel into the pocket of each electrode. After completion of an experiment, it is necessary to clean the headset by removing the gel and cleaning the electrodes. This is often done with alcohol because of its evaporative properties [3,4].

Saline solution: Some of the EEG headsets require a conductive gel to help make low-impedance electrical contact between the skin and the sensor electrode. EEG headsets that have this technology connect electrodes by applying saline to each electrode [3,4].

Dry: Dry EEG devices do not use any gel or saline to connect the electrodes with the scalp, which makes it easier to record EEG data without the help of a trained technician [3,4]. Furthermore, its setup time is considerably shorter than wet headsets.

Others: Some EEG sensor connections types do not fit cleanly into either of these two categories. Conductive solid gel materials, such as those produced by Enobio, have also been used successfully in EEG devices.

2.2. Differences between Dry and Wet Devices

In January of 2019, researchers at the University of California, The Otto von Guericke University of Magdeburg, and The Hebrew University of Jerusalem performed a comparative analysis of the signal quality of dried wireless and wet wire EEG devices, and concluded that the quality of wireless dry devices is significantly comparable with the wired wet. Although some researchers observed that, for those activities that demand body movement like running/walking, wired wet sensors showed better performance [5,6]. This seems to indicate that wet sensors may be more resistant to movement artifacts, although more research needs to be conducted to fully understand which technology can provide more reliable data.

2.3. Electrode Placement Standards

The American clinical neurophysiology society suggested two international placements of electrodes on the scalp: 10–20 and 10–10 standards [7]. The numbers refer to the distances between adjacent electrodes placed on the skull. For example, for the 10–20 standard, the relative distance between an electrode and the underlying area on the skull is either 10% or 20% [7,8]. The electrode location starts with a letter, followed by odd or even numbers to indicate the placement and the left or right side of the brain, including: F (frontal), C (central), T (temporal), P (posterior), and O (occipital) [9]. Figure 2 shows the name and position of each electrode in the 10–20 (black circles) and in 10–10 system (gray circles) [8]. The 10–20 system is suitable for both clinical and non-clinical studies and event-related potentials studies (ERPs) [8]. The 10–10 system is suitable for obtaining more detailed EEG data [7,9].

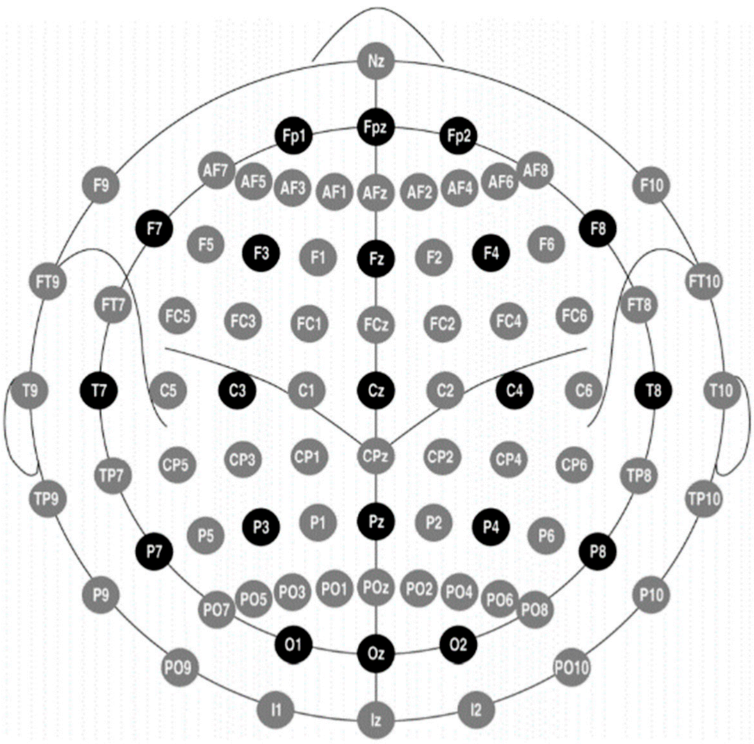

Figure 2. Electrode positions and labels in the 10 ± 20 system [8].

2.4. EEG Devices with Several Sensors

Some EEG devices are designed to capture both psychological (brain) and physiological (blood pressure, muscle activity, heart rate, etc.) data. These devices have one or more extra channels for capturing physiological signals such as Electrocardiogram (ECG), Electrooculography (EOG), Photoplethysmogram (PPG), and Electromyography (EMG).

ECG sensors record the heart's response during resting or physical activity.
EOG sensors measure human eye movements.
PPG sensors monitor blood volume changes.
EMG sensors collect muscle activity data.

Some EEG devices are equipped with motion sensors such as gyroscopes and accelerometers to capture head and body motion data. These can be used to measure, e.g., orientation, acceleration, and speed.

3. Applications of EEG

EEG devices can provide valuable information about human mental health states, thoughts, and imagination. Thus, researchers in different areas of research have utilized it. Figure 3 demonstrates five categories of EEG data applications and their relevant sub-categories. In a later section, *EEG Headset Applications and Research Usages*, a report of relative research use for various devices is provided as part of a table.

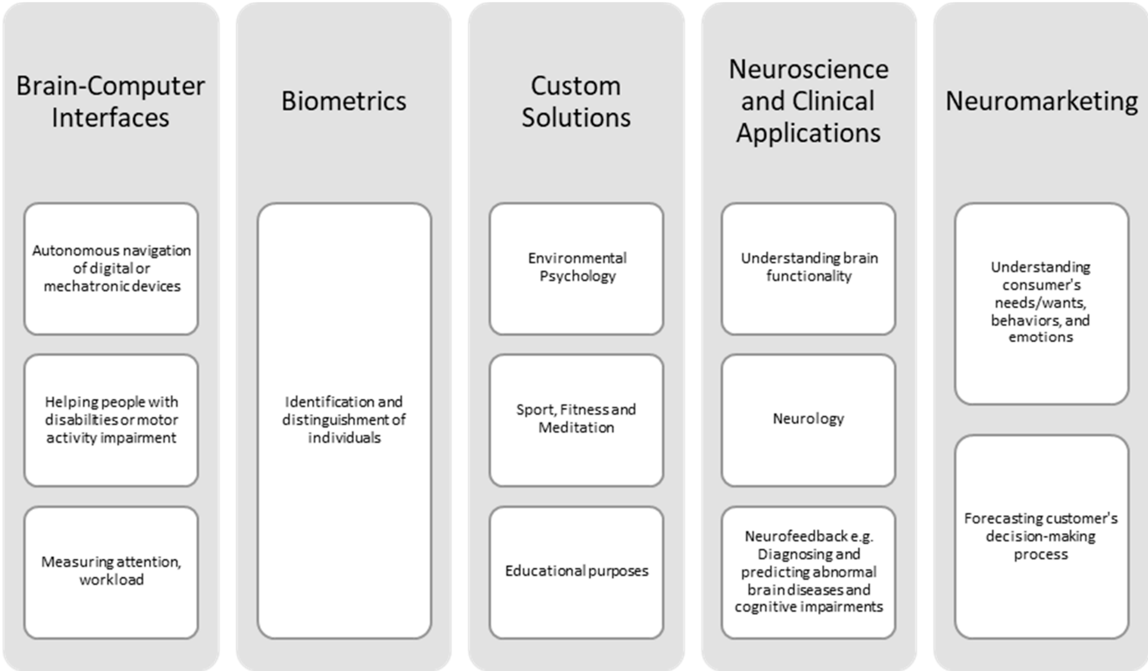

Figure 3. Electroencephalography (EEG) applications.

Brain–computer interfaces (BCI): BCIs, sometimes called brain–machine interfaces (BMIs), are one of the most common applications of EEG. BCIs use real-time EEG data to control and direct mechanical and electronic devices [10–17].

BCI devices are commonly used as a human–machine interface to help individuals with mild to severe motor disabilities, including those who are not able to communicate with others [10]. BCI devices designed for the disabled do not rely on muscle movements; instead, they use specific brain activity, imagining doing an activity, or concentrating on an object on-screen, and translate them into control functions and commands [10,11].

The most common BCI applications are listed below.

1. **Autonomous navigation of digital or mechatronic devices:**
   - Real-time teleoperation of robotic body parts [18–22];
   - Controlling and directing a robot [23–26], drone [27], dashboard of a vehicle [28], or a miniature or semi-automated car [29,30];
   - Monitoring and controlling sensors inside of smart houses [31].
2. **Helping people with disabilities or motor activity impairment:**
   - Control of mobile phone apps using eyewinks [32];
   - Directing electrical wheelchair movement [33–36];
   - Control of artificial body part such as prosthetic hand or arm [10,37,38];
   - Recognizing a patient's attempt to move their body, e.g., stroke [39] and brain injury [40];
   - Post-stroke motor rehabilitation using VR [41];
   - Controlling a robot using body gestures [42];
   - Mind-controlled dialing systems [43];
   - Speech recognition system for people with speech disability [12,44];
   - Mouse cursor control using imagined hand movement [45];
   - Gaze controller for patients with neurodegenerative diseases [46].

3. **Neurogaming and Entertainment**

    - Controlling a video game or virtual reality (VR) environment using body gesture and eye movement [47];
    - Controlling fiber optic clothes or dresses [19].

Neurology: Real-time EEG signals can be used to provide immediate information about brain-wave activities. EEG data have been applied for diagnosing and predicting many abnormal brain diseases and cognitive impairments, listed below:

- Epilepsy [48];
- Parkinson's Disease [49];
- Memory problems like Alzheimer's [50];
- Language impairments such as Dyslexia [51];
- Attention Deficit Hyperactivity Disorder (ADHD) [52];
- Seizures [12];
- Schizophrenia [53];
- Autism in adults and children [54,55];
- Sleep disorders and insomnia [56,57];
- Anxiety [58];
- Post-traumatic stress disorder [10];
- Huntington's disease [59];
- Multiple sclerosis diagnosis [60];
- Amyotrophic lateral sclerosis [61];
- Traumatic brain injury (TBI) [62];
- Coma [63];
- Level of consciousness [64];
- Neurosurgery [65].

Neuroscience Research: Neuroscience attempts to understand the functionality of the nervous system. It allows clinical or non-clinical researchers to get an idea about how the brain acts when humans experience different emotional states and how the brain works in various mental states. Researchers have applied EEG devices in their studies in the below fields.

1. Cognitive neuroscience:

    - Measuring cognitive load [28,66,67];
    - Detecting differences between brain wave activity during suicidal and non-suicidal states [68]. Understanding brain activity during insight (insight is a moment where a human understands how to solve a puzzle or gains knowledge) [69];
    - Analyzing brain workload during decision making or learning a new task [60,70,71];
    - Studying sleep pattern [72];

2. Behavioral neuroscience:

    - Changing the workplace light and measuring brain alertness status [73];
    - Measuring drowsiness or sleep detection for drivers and pilots [74];
    - Measuring mental workload of deaf children exposed to a noisy environment during a word recognition task [75];
    - Determining surgeon stress level while performing surgery [76];
    - Identifying and reducing stress level [77];
    - Environmental Psychology [78].

3. Neurophysiology:

    - Measuring changes in brain after drinking alcohol [79];
    - Detecting fatigue [74].

Neuroscience can also be applied to understanding human emotion in VR with/without the ability to touch the environment [80,81] by displaying various types of media, such as:

- Real world or VR pictures [82];
- Images of nature and city environments [32];
- TV advertisements [36];
- Auditory stimuli [83];
- Multimedia [36,47,69], along with memory recall and dreams [84].

Neuromarketing or Consumer Neuroscience: Neuromarketing, one of the newest branches of the advertising industry, aims to understand the consumer's needs, behaviors and emotions, and forecast their decision-making processes [81,85–87]. Some neuromarketing research attempts to understand customers' preferences and expectations regarding a specific product [81] and their reaction to TV advertising by analyzing EEG signals [86,87].

Biometrics: Recognizing and distinguishing people using physiological or behavioral features such as fingerprint, voice, face, iris, gaze, gait and/or posture is called biometrics [71,88,89]. Studies show that EEG data can provide information about individuals' differences. Recently, cognitive and emotional brain status has been utilized for biometrics, meaning EEG data are used to identify people [89]. The main ideas behind why EEG-based biometric systems have received more attention recently relate to privacy compliance and robustness to spoofing attacks, as well as universality [88,89].

Custom Solutions and Neurofeedback (Neurotherapy): EEG devices have been applied in other areas of research to make a comfortable environment, improve well-being and life quality, and boost the learning process. Neurofeedback data can be used for either clinical or non-clinical research. Some customized EEG solutions are listed:

1. **Sport, fitness and meditation:** Monitoring health status and boosting quality of life using brain activity during exercise and listening to music [83].
2. **Educational purposes:**

    i. Measuring the reading ability of students [84];
    ii. Measuring confusion level during online lectures [90] or concentration level and cognitive workload when students are trying to solve a math puzzle [91] with the aim of designing intelligent tutor systems (ITS);
    iii. Real-time brain visualization, which can have educational, training, or entertainment applications [92,93].

Figure 4 shows the most popular research topics of EEG data, as found by an internet search of "EEG" followed by each keyword in the pie chart of the figure. It is clear that after neuroscience, BCIs have received the most attention from researchers, and the percentage of studies on biometrics and neuro-marketing fields is relatively small.

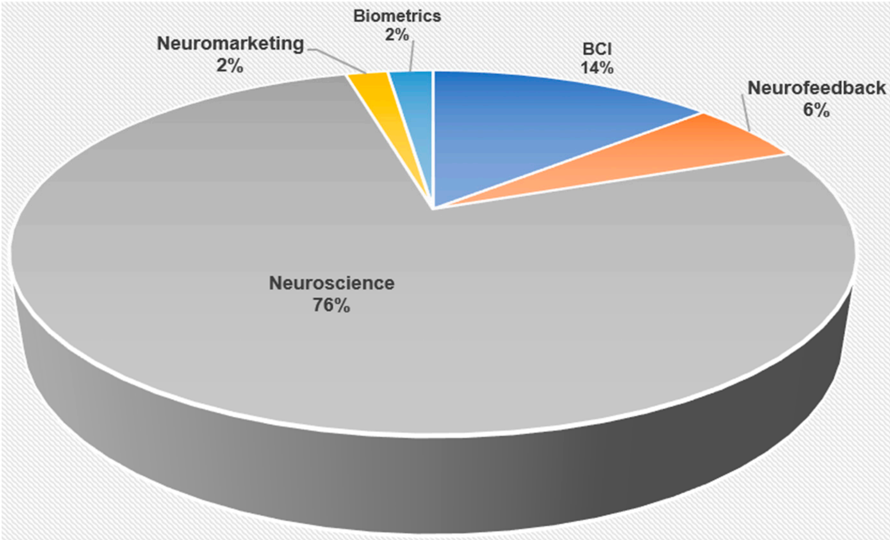

Figure 4. Percentage of each topic found through internet keyword search.

4. EEG Headset Applications and Research Usages

There are many commercially available EEG headsets. In the following, a set of tables shows the approximate applications for each headset, as well as their specifications and relative research use. In general, information was gathered from the company website for each product.

Table 1 indicates the applications that each EEG Headset has been used in, according to the producing company's reports.

Table 1. Recommended EEG application by manufactured company.

Applications (Company Recommendation)	EEG Headset Product Name (Company)
Neuroscience Research	• DSI 24, DSI 7, DSI 7 Flex, VR300 (Wearable Sensing) • B-Alert X-Series (Advanced Brain Monitoring) • Enobio (Neuroelectrics) • Eego mylab (ANT Neuro) • Imec product • SMARTFONES, SMARTING (mBrainTrain)
Neuromarketing	• DSI 24, DSI 7 (Wearable Sensing) • B-Alert X-Series (Advanced Brain Monitoring) • SMARTFONES, SMARTING (mBrainTrain)
Brain computer interface and Neurogaming	• DSI 24, DSI 7, VR300, NeuroCube, NeusenW (Wearable Sensing) • Epoc ^{X}, Epoc $^{+}$, Epoc ^{Flex}, INSIGHT (Emotiv) • B-Alert X-Series (Advanced Brain Monitoring) • Enobio (Neuroelectrics) • MindWave, MindWave Mobile 2 (NeuroSky) • BrainWaveBank products • NeusenW (wearable sensing) • Eego mylab, Eego^{TM} mini-series (ANT Neuro) • SMARTFONES, SMARTING (mBrainTrain)

Table 1. *Cont.*

Applications (Company Recommendation)	EEG Headset Product Name (Company)
Ergonomics and Biometrics	• DSI 24, DSI 7 (Wearable Sensing) • B-Alert X-Series (Advanced Brain Monitoring)
Neurofeedback	• DSI 24, DSI 7 (Wearable Sensing) • Sleep studies: EEG Electrode Cap Kit (OPENBCI), Sleep Profiler PSG2™, Sleep Profiler™ (Advanced Brain Monitoring), Muse 2, Muse S (Muse ™), LiveAmp (Brain Products), BE Micro (EB Neuro) • Enobio (Neuroelectrics) • MindWave Mobile 2 (NeuroSky) • Eego mylab (ANT Neuro) • Imec product • SMARTFONES, SMARTING (mBrainTrain)
Biofeedback	• Meditation and Sleep studies: Muse 2, Muse S (Muse ™) • Cardiology and Gastroenterology: BE Micro (EB Neuro)
Custom Solutions (e.g., Sports, education)	• DSI 7 Flex (Wearable Sensing) • Enobio (Neuroelectrics) • MindWave, MindWave Mobile 2 (NeuroSky) • Eego mylab (ANT Neuro)

Table 2 provides information about the characteristics of the available EEG headsets\caps, such as number of channels, sampling rate, electrode connection type, headset preparation time (the amount of time it takes to prepare the headset/cap), and price. Some of the EEG devices are equipped with extra sensors, enabling them to track muscle activities (EMG), heart rate (ECG), eye movement (EOG), and blood pressure (PPG); these are indicated in the "Extra Sensors" column. The "Motion Sensors" column shows any EEG devices that have motion sensors, such as an accelerometer or gyroscope, for tracking body or head movement. The "Communication Mode" column indicates the way in which the sensor transfers its recorded data. If the EEG device is a wireless Bluetooth device, it works in a specific range, and outside of that distance, may not work correctly; this information is shown in the "Bluetooth range" column. The "Battery life" column shows how many hours the device is capable of working for using its wireless technology. For some companies, such as Compumedics Neuroscan, the listed EEG devices are only components of the full device, which is necessary to perform Electroencephalography, such as cap and amplifier, thus cannot be used without the purchase of separate hardware.

Some of the EEG devices have included open source software, allowing users to capture and analyze the data for free, while for some headset/caps, users need to pay subscription fees and/or purchase the related software; this information is denoted in the "Included Software" column.

Table 2. Sensors information.

Company	Product Name	Extra Sensors (Optional)	Motion Sensors	Communication Mode(s)	Bluetooth Range	Included Software	Battery Life (When Applicable)
Compumedics Neuroscan	Quick-Cap Neo Net	EOG ECG EMG	-	-	-	-	-
	Quick-cap Silicone Array	EOG ECG EMG	-	-	-	-	-
	Quick-Cap Hydro Net	EOG ECG EMG	-	-	-	-	-
	Quick-Cap	EOG ECG EMG	-	-	-	-	-
Wearable sensing	DSI 24	EMG EOG ECG	Accelerometer (Opt)	Bluetooth Wireless	10 m/30 feet	DSI-Streamer Data Acquisition Software and API	-
	DSI 7	N/A	Accelerometer (Opt)	Bluetooth Wireless	10 m/30 feet	DSI-Streamer Data Acquisition Software and API	-
	DSI 7 Flex	N/A	Accelerometer (Opt)	Bluetooth Wireless	10 m/30 feet	DSI-Streamer Data Acquisition Software and API	-
	VR300	N/A	Accelerometer (Opt)	Bluetooth Wireless	10 m/30 feet	DSI-Streamer Data Acquisition Software, API, and Unity and Unreal SDK for VR	-
	NeusenW	N/A	9-axis motion sensors	Bluetooth Wireless	-	-	Up to 2 h
	NeuroCube	N/A	9-axis motion sensors	Bluetooth Wireless	-	-	Up to 2 h
Emotiv	EPOC X	N/A	9-axis motion sensors	Bluetooth Wireless	-	EmotivPRO Emotiv BrainViz	Up to 9 h
	EPOC $^{+}$	N/A	3-axis Accelerometer	Bluetooth Wireless	-	EmotivPRO EmotivBCI Emotiv BrainViz	Up to 12 h
	MN8	N/A	Motion sensors	Bluetooth Wireless	-	-	Up to 6 h

Table 2. *Cont.*

Company	Product Name	Extra Sensors (Optional)	Motion Sensors	Communication Mode(s)	Bluetooth Range	Included Software	Battery Life (When Applicable)
	INSIGHT	N/A	9-axis Motion sensors	Bluetooth Wireless	-	-	Up to 9 h
	EPOC ^{Flex}	N/A	3-axis Accelerometer, Magnetometer	Bluetooth Wireless	-	EmotivPRO	Up to 9 h
OPEN BCI	EEG Electrode Cap Kit	N/A	N/A	Bluetooth Wireless	-	OpenBCI's FREE open-source software	-
	Ultracortex "Mark IV" EEG headset	EMG ECG	3-axis Accelerometer	Bluetooth Wireless	-	-	-
	OpenBCI Classroom Bundle (5 kits)	EMG ECG	N/A	Bluetooth Wireless	-	-	-
Biosemi	ActiveTwo	EMG ECG	N/A	Wired	-	LabVIEW	N/A
	ActiveOne	EMG ECG	N/A	Wired	-		N/A
Advanced Brain Monitoring	Sleep Profiler™	EOG EMG ECG	N/A	Wireless	-	-	Up to 30 h
	Sleep Profiler PSG2TM	EEG EOG EMG	N/A	Wireless	-	-	Up to 30 h
	Stat X-Series	ECG EOG EMG	Accelerometer	Bluetooth Wireless	10 m	B-AlertLive LabX	Up to 8 h
	B-Alert X-Series	ECG EOG EMG	Accelerometer	Bluetooth Wireless	10 m	B-AlertLive LabX	Up to 8 h
InteraXon	Muse S	PPG	Accelerometer Gyroscope	Bluetooth Wireless	-	Muse App	10 h
	Muse S Bundle	PPG	Accelerometer Gyroscope	Bluetooth Wireless	-	Muse App	10 h
	Muse 2	PPG	Accelerometer Gyroscope	Bluetooth Wireless	-	Muse App	5 h

Table 2. *Cont.*

Company	Product Name	Extra Sensors (Optional)	Motion Sensors	Communication Mode(s)	Bluetooth Range	Included Software	Battery Life (When Applicable)
Neuroelectrics	Enobio	N/A	3-axis Accelerometer	Bluetooth Wireless	-	Enobio API Matlab (EEGLAB Plugin) Python (Neyp library)	Up to 20 h
NeuroSky	MindWave Mobile 2	ECG	N/A	Bluetooth Wireless	10 m	MindWave Mobile apps	8 h
Wearable Sensing	NeusenW	EOG	9-axis motion sensor	Bluetooth Wireless	-	-	-
ANT Neuro	Eego^{TM} mylab	N/A	N/A	Bluetooth Wireless	-	API	Up to 5 h
	Eego^{TM} sports	EMG	N/A	Bluetooth Wireless	-	API	Up to 5 h
	Eego^{TM} mini-series	EMG	N/A	Bluetooth Wireless	-	API	Up to 5 h
G.tec	NAUTILUS FNIRS	N/A	3-axis accelerometer	Bluetooth Wireless	10 m	BSANALYZE	Up to 10 h
	Nautilus Research	N/A	3-axis accelerometer	Bluetooth Wireless	0 m	BSANALYZE	Up to 6 h
	Nautilus PRO	N/A	3-axis accelerometer	Bluetooth Wireless	10 m	BSANALYZE	Up to 10 h
	G. nautilus multi purpose	N/A	3-axis accelerometer	Bluetooth Wireless	10 m	BSANALYZE	-
imec	-	N/A	-	Bluetooth Wireless	-	Qt-based, MS & Android	Up to 8 h
EB Neuro	BE Micro	-	N/A	Bluetooth Wireless	-	-	Up tp 72 h
mBrain Train	SMARTING	N/A	3 axis gyroscope	Bluetooth Wireless	10 m	API	Up to 5 h
	SMARTFONES	N/A	N/A	Bluetooth Wireless	-	API	-
	SMARTING sleep	ECG EMG EOG	9 axis motion sensor	Bluetooth Wireless	10 m	API	Up to 15 h

Table 2. *Cont.*

Company	Product Name	Extra Sensors (Optional)	Motion Sensors	Communication Mode(s)	Bluetooth Range	Included Software	Battery Life (When Applicable)
Cognionics (CGX)	Quick	EOG ECG EMG PPG GSR	N/A	Bluetooth Wireless	-	-	-
	Mobile	EOG ECG EMG PPG GSR	N/A	Bluetooth Wireless	-	-	-
Brain Product	actiCAP (Slim & Snap)	N/A	N/A	-	-	-	-
	LiveAMP	N/A	N/A	Bluetooth Wireless	-	-	-

In Table 3, publication numbers were found through an internet query of the name of the company followed by the product name; the numbers provided in the "Company name" column are the search results with only the company name. The relationship between the 'company-only' search results alongside the 'company-and-product' search results is important to note, as the nature of some company's names are such that the search results do not accurately reflect their influence on the research. To avoid searches that include individual words not reflective of the company or product being searched for, quotation marks were added around the search term. Additionally, the "MD" column indicates if the mentioned EEG device can be used for clinical research, meaning it has been FDA approved. This is indicated either by an X, meaning that the device has not been officially approved, or by a ✔, indicating that the device has been approved.

Information about sampling rate, number of channels, set up time, and price is also provided. An N/A indicates that the information does not apply, and a "-" symbol indicates that the searchers were unable to ascertain the information.

Table 3. List of EEG headsets.

Company	Publications (Company)	EEG Headset/Caps	No. Publications	MD [1]	Sample Rate	No. Channels	Electrode Connection Type	Set up Time: Minutes(m) or Seconds (s)	Price
Compumedics Neuroscan		Quick_Cap Neo Net		X		Up to 256	Gel	-	-
		Quick_Cap Silicone Array		X		Up to 256	Saline	-	-
		Quick_Cap Hydro Net		X		Up to 256	Saline	-	-
		Quick-Cap		X		Up to 256	Gel	-	-
Emotiv	8150	INSIGHT	362	X	128 Hz	5	Semi-dry polymer	1–2 m	$299
		EPOC X	1	X	128 Hz	14	Wet (Saline)	3–5 m	$849
		EPOC+	4370	X	128 Hz	14	Saline soaked felt	3–5 m	$699
		EPOC FLEX KIT	0	X	128 Hz	32	Saline/Gel	15–30 m	$1699
		MN8	0	X	-	2 (+4 reference)	Dry	30 s	-
OpenBCI	835	Ulracortex Mark IV	26	X	125 HZ or 250 Hz	8 or 16	Dry	~30 s	Print-It-Yourself ($299.99–399.99)
									Unassembled ($499.99–599.99)
									Pro-Assembled ($699.99–849.99)
		EEG Electrode Cap Kit	1	X		21	Gel	~30 s	$399.99
BIOSEMI	10,300	ActiveTwo	2650	X	2, 4, 8, 16 kHz	280	Gel	-	€ 14,840 € 72,440
		ActiveOne	15	-	-	Up to 144	Gel	-	
Advanced Brain Monitoring	2030	B-Allert (X10 or X24)	37	✔	256 Hz	9 and 24	Dry	-	$1000–$25,000
		Sleep Profiler	2	✔	-	Up to 8	Dry	-	-
		Sleep Profiler PSG2TM	0	✔	-	Up to 13	Dry	-	-
		Stat X-Series	0	✔	-	Up to 20	Dry	-	-

Table 3. *Cont.*

Company	Publications (Company)	EEG Headset/Caps	No. Publications	MD [1]	Sample Rate	No. Channels	Electrode Connection Type	Set up Time: Minutes(m) or Seconds (s)	Price
InteraXon	1140	Muse 2	158	X	220 Hz or 500 Hz	4	Dry	-	$224.99
		Muse S Bunddle		X	-	4	Dry	-	$444.98
		Muse S		X	-	4	Dry	-	$344.99
Neuroelectrics	1200	Enobio	59	✔	500 SPS	8, 20, 32	Dry/Wet	-	-
G·tec	4950	Nautilus Research	16	X	250 Hz or 500 Hz	8, 16, 32, 64	Gel	-	$1000–$25,000
		NAUTILUS FNIRS		X	250 Hz or 500 Hz	8, 16, 32, 64	Wet	-	-
		Nautilus PRO		✔	500 Hz	8, 16, and 32	Dry/Wet	-	-
		Nautilus multi-purpose		X	250 Hz or 500 Hz	8, 16, 32, 64	Wet	-	-
Cognionics (CGX)	497	QUICK	49	X	500 Hz or 1000 Hz	8, 20, 30	Dry	-	$1000–$25,000
		Mobile	21	X	500 Hz or 1000 Hz	64, 128	Gel	-	-
ANT Neuro	1110	eego mylab	8	X	16 kHZ	32–256	Dry/Gel	-	$1000–$25,000
		Eego™ sports	10	X	-	-	-	-	-
		Eego™ mini-series	-	X	-	-	-	20 m	-
Brain Products	11,700	LiveAmp	31	X	250–1000 Hz	8–64	Dry/Gel		$1000–$25,000
		ActiCAP	899	X	-	-	-	-	-
Wearable Sensing	1220	Dry Sensor Interface Series	0	X	300–600 Hz	2–21	Dry	~5 min.	$1000–$25,000
		VR300	-	X	300 Hz	7	Dry	1–3 min	-
		NeusenW	-	-	Up to 16 kHz	8–64	Wet	-	-
		NeuroCub	-	-	16 kHz	8	Wet	-	-
		DSI 24	18	-	300 Hz	21	Dry active hybrid	3–5 min	-
		DSI 7 Flex	-	-	300–600 Hz	-	Dry	-	-
		DSI 7	5	-	300–600 Hz	2–6	Dry	1–3 min	-
NeuroSky	4910	MindWave Mobile 2	1510	-	150 Hz	2	Dry	-	-

Table 3. *Cont.*

Company	Publications (Company)	EEG Headset/Caps	No. Publications	MD [1]	Sample Rate	No. Channels	Electrode Connection Type	Set up Time: Minutes(m) or Seconds (s)	Price
BrainWave Bank	7	-	-	-	-	16	-	~5 m	-
imec	92,200 [2] (1690)	EEG Headset	17	-	128, 256, 1028 Hz	8	Dry	-	-
EBNeuro	367	BE Micro	57	-	-	-	-	-	-
mBrainTrain	159	SMARTING	99	-	250–500 Hz	24	-	-	-
		SMARTFONES	1	-	Up to 1000 Hz	11	Semi-dry	-	-
		SMARTING sleep	-	-	250–500 Hz	17	Dry	-	-

[1] MD certified might be for diagnostic or for Clinical Treatment. [2] The results for the "imec" query were deemed too vague to be of use, so the term "EEG" was added outside of the quotation marks; the parenthetical number is the result of this search.

5. Discussion

To select an EEG device, it is necessary to look at a variety of factors, some of which are listed below:

- **Designing Technology Dry/Wet (saline or gel):** Unfortunately, there are few studies done on this area. Recently, some researchers [35,37] compared a dry and wet headset for their research and they concluded that although the selected dry EEG headset was more robust to line noise, it contained more artifacts;
- **Setup time:** Regardless of the connection type being used, the setup time for EEG electrodes tends to be longer than for most physiological sensors. Saline-based sensors are usually selected for their ease of use and quick setup time, relative to gel-based sensors. Gel based EEG devices demand a larger amount of time, relative to other connection methods, to apply, while the saline headset does not take much time to set up. Cleaning saline headsets after using them takes less time than gel-based sensors. The gel also sticks to the hair of participants, which could be uncomfortable and inconvenient for users;
- **Signal quality and stability:** Quality of the captured EEG data depends on several factors: connection stability, losing connection with the scalp, and wireless, which are described below:

    1. **Losing Connection with the Scalp:** The quality of the recorded EEG data highly depends on the connection between electrodes and the scalp. Gel-based sensors are usually chosen for their stability of connection and longevity, as the wet or gel-based sensors maintain a more stable connection for several hours, while wet and dry EEG headsets may lose humidity during an experiment, which can lead to a decline in signal quality. To have stable, high-quality and reliable EEG data, it is necessary to make sure that all relevant electrodes are connected and do not lose their connection during experiments by reapplying the saline solution to the electrodes, as the solution evaporates over time. In order to maintain a stable connection over long periods, it is necessary to reapply the saline solution to the electrodes, as the solution evaporates over time;
    2. **Wireless Connectivity:** Wireless EEG devices can pose a security risk to the data of the participant, as any movement of cables could potentially induce the data during transfer. Because of this, wireless EEG devices should necessarily require encryption of the data prior to wireless transfer.

- **Headset Size:** Most EEG devices are limited in their size adjustability, and may thus require multiple different caps or headsets in order to fit experiments and studies which collect data of individuals with large head-size discrepancies, increasing the overall price;
- **Battery Life:** Wireless EEG devices are most often battery-operated and, as such, are subject to potential loss of data if the current battery charge falls below threshold levels. Ensuring that batteries will be operational throughout long studies can be difficult, and the necessity of ensuring batteries are charged increases the complexity of data-gathering using EEG devices. Battery life has a negative correlation with the amount of sensory information they provide; as more information is given, the battery time decreases, which means that the research focused on long-term study of brain activities should try to rely on less sensory information, if possible;
- **Sensitivity to external noise/artifacts:** When collecting EEG data, it is important to ask the participants to sit in a relaxed manner because any movement of the body can cause artifacts in the data. To obtain high-quality data and better results, artifacts such as muscle and eye movement, eye blink, and line noise need to be pre-processed and artifacts should be omitted before doing any data analysis;
- **Price:** Most of the EEG devices designed for medical purposes like Neurofeedback and neuroscience are expensive;

- **API/Software Used by Device:** The software which accompanies an EEG headset can be complicated for researchers without prior extensive knowledge about brain activity, as well as knowledge of filtering and analysis techniques. The software, which is utilized by an EEG device, can have adverse effects on the ease and reliability of experiments, as well as the overall cost. In addition to research on the quality of the EEG device itself, care should be taken to understand if the software it makes use of is within acceptable cost and quality levels. Open Source software tends to be more secure, but has less built-in support for newer users, whereas integrated proprietary software tends to have better support, but is more costly. Depending on the EEG software, users may be given access to raw EEG data that has not been modified, processed data that has been modified after recording by the software in some way, or to both raw and processed data;
- **Comfort to user:** Wireless dry or saline solution EEG devices are more convenient for the user because of their flexibility of movement, lower setup time, and no need for cleaning the user hairs after the experiment like in gel-based solution;
- **CE/FDA approved:** Most of the listed commercial EEG sensors have not been CE/FDA approved. A list of EEG headsets that can be utilized for clinical treatments is given in the "MD" column of Table 3.

6. Conclusions and Future Research

EEG devices are quickly becoming less expensive and more accessible to the open market, which should allow for more commercial and personal use of the data. Because of their widespread availability, many considerations should be made before a decision is made to purchase and use a device. Along with price, other factors that need to be considered are the battery life of an EEG device, available software for data analysis, and common uses of the device in research areas, especially where your own research may apply.

For future research, areas like biometrics and neuro-marketing currently have very little related research, and thus may be good avenues for further study.

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