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# Wireless EEG: A survey of systems and studies

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ABSTRACT

The popular brain monitoring method of electroencephalography (EEG) has seen a surge in commercial attention in recent years, focusing mostly on hardware miniaturization. This has led to a varied landscape of portable EEG devices with wireless capability, allowing them to be used by relatively unconstrained users in real-life conditions outside of the laboratory. The wide availability and relative affordability of these devices provide a low entry threshold for newcomers to the field of EEG research. The large device variety and the at times opaque communication from their manufacturers, however, can make it difficult to obtain an overview of this hardware landscape. Similarly, given the breadth of existing (wireless) EEG knowledge and research, it can be challenging to get started with novel ideas. Therefore, this paper first provides a list of 48 wireless EEG devices along with a number of important—sometimes difficult-to-obtain—features and characteristics to enable their side-by-side comparison, along with a brief introduction to each of these aspects and how they may influence one's decision. Secondly, we have surveyed previous literature and focused on 110 high-impact journal publications making use of wireless EEG, which we categorized by application and analyzed for device used, number of channels, sample size, and participant mobility. Together, these provide a basis for informed decision making with respect to hardware and experimental precedents when considering new, wireless EEG devices and research. At the same time, this paper provides background material and commentary about pitfalls and caveats regarding this increasingly accessible line of research.

## 1. Introduction

Electroencephalography (abbreviated EEG) is a brain monitoring modality with an almost 100-year history of human application (Berger, 1929), and experiences go even further back in time if we include animal studies (e.g., Caton 1875). The recorded electroencephalogram (also abbreviated EEG) reflects the postsynaptic activity of large groups of neurons in the cerebral cortex, allowing a subset of brain activity to be recorded, analyzed, and in some cases even decoded, with applications in medical, research, and consumer fields.

Throughout its long history, EEG has seen continuous improvements, primarily with respect to methodology on the one hand, and hardware on the other.

Methodologically, where early analyses involved the measurement of the EEG signal's peaks and troughs with ruler and pen on rolls of standardized graph paper, much has changed with the introduction of programmable computers. The first major computer-aided paradigm shift was probably the introduction of the event-related potential (ERP) technique, which allowed the brain's responses to individual events to be revealed and investigated. One advantage of this technique is that a larger number of single event-related responses can be collected and averaged, providing a detailed look at the time course of specific neural processes. (See Luck's (2014) excellent book for a detailed introduction to this technique). A further breakthrough was the ability to detect such brain responses in single trials: without relying on averages, specifically designed signal processing pipelines could be constructed to distinguish between two or more predefined classes of responses. This was first demonstrated by Vidal (1977), and especially following the success of novel machine learning algorithms (e.g., Lotte et al. 2018), this led to a variety of so-called brain-computer interface (BCI) systems and applications. Originally, these have largely been aimed at medical interventions (e.g., neuroprosthetics, neurorehabilitation; Soekadar et al., 2015; Cervera et al., 2018; Jamil et al., 2021), but today, EEG and BCI applications can additionally be found in industrial and commercial fields,

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e.g. neuroergonomics (Parasuraman, 2003), neuromarketing (Lee et al., 2007), sports (Thompson et al., 2008), and so-called passive BCI for everyday and human-computer interaction applications (Zander and Kothe, 2011; Krol et al., 2018). As a final example of the many methodological advances the modality has seen over the past decades, EEG has been a prime candidate for mobile brain-body imaging (MoBI), where measures of brain activity are combined with additional measures of physiological, muscular, and/or behavioral activity in order to investigate embodied cognition (Makeig et al., 2009; Gramann et al., 2014). This goes hand in hand with the development of new signal processing methods that, e.g., allow environmental noise to be removed (Klug and Kloosterman, 2022) and brain activity to be separated from artifactual signals (Makeig et al., 1995).

Taken together, these and many other methodological improvements make it possible to, today, use EEG not just for academic purposes, but for a large variety of scientific, medical, industrial, and commercial applications. That is, these things are possible *in principle*: in practice, one of the main obstacles to the everyday use of EEG remains the restrictive form factor of most EEG hardware. Here, too, however, significant progress has been made in recent decades.

In the earliest days, human EEG recordings used a trepanation or burr hole through the skull for the electrodes to be close enough to the cortex to record its activity. After that, for a long time, it remained common practice to remove or otherwise puncture the outer surface layer of the skin to reduce the influence of noise, because, among other reasons, computers were not yet available to filter this out post hoc. However, advances in both electrode and amplifier technology, as well as health standards, have long since allowed for high-quality EEG to be recorded completely non-invasively. Modern EEG typically requires little more than applying conductive gel between each electrode and the scalp, and a 64-channel setup may be prepared in as little as half an hour. So-called active electrodes include small pre-amplifiers to further increase the signal-to-noise ratio, and active shielding techniques may be used to further protect the recorded signal from environmental artefacts. More recently, alternative types of electrodes have also been developed that do not even require gel, but instead use a simple saline solution (so-called wet electrodes), or indeed nothing at all (dry electrodes). With respect to amplifiers, the most noticeable recent trend is one of miniaturization. Early EEG amplifiers could be the size of a large armoire, and even modern-day stationary amplifiers (plus battery) can weigh a few kilos. But, following emerging research (e.g., MoBI) and clinical needs, and as neurotechnology finds applications in other fields as mentioned above, both established companies and commercial newcomers are developing ever smaller, even wearable EEG amplifiers. Ideally, such devices will allow the large body of EEG research of the past century to be translated into real-world applications, outside of the laboratory, unhindered by the constraints imposed by the old, unwieldy machines.

This, then, is the topic of this paper: the wireless EEG device. We use 'wireless' here in the sense defined below. There is some difficulty in providing an objective definition to characterise the large, heterogeneous group of small, modern EEG devices that are designed for increased participant mobility (Bateson et al., 2017).

We may first follow the terminology used by Bleichner and Debener (2017), who provided the following distinction between mobile, portable, wearable, and transparent EEG. Here, *mobile EEG* refers to EEG 'technology that does not require the user to remain still', but instead 'tolerate[s] at least a modest degree of motion movement during signal acquisition' (Bleichner and Debener, 2017). A mobile EEG setup could include, for example, a stationary EEG amplifier recording from a person walking on a treadmill (Gramann et al., 2014). *Portable EEG* on the other hand denotes that the whole set-up can 'easily be carried around' (as e.g. in Debener et al. 2012a, De Vos et al. 2014a). This is primarily a function of size: as Bleichner and Debener (2017) point out, it does not necessarily mean that the device is also tolerant of motion. A third category of *wearable EEG* refers to a subset of portable EEG with a 'self-fitting characteristic', allowing users to apply it themselves and making it suitable to be worn alongside regular clothing. Finally Bleichner and Debener (2017), suggest that *transparent EEG* combines all of the above: it refers to a 'portable, motion-tolerant, self-applicable' device which, on top of that, is 'highly unobtrusive, near invisible, and comfortable to wear'.

Since some of the above characteristics are difficult to objectively quantify, in this paper, we use the term *wireless EEG* to refer to EEG devices that support wireless protocols for signal acquisition. In practice, this means that the term wireless EEG generally refers to any and all of the above categories, since the presence of such a wireless protocol is a clear indication that the device is intended to be either mobile, portable, wearable, or a combination thereof. Essentially, we interpret the inclusion of a wireless protocol to signify the manufacturer's intention to allow for significant degrees of device and participant mobility. Often, this mobility is ultimately the most important characteristic of these devices: it allows EEG to be recorded with fewer hurdles, fewer restrictions, and fewer distractions, to eventually enable the real-world applications mentioned above.

The recent availability of various wireless EEG devices allows experienced EEG researchers to expand their research beyond laboratory conditions, and provides researchers from other disciplines a lower threshold to incorporate EEG signals in their investigations and applications. This paper is aimed primarily at the latter group, but aims to provide an objective, general overview of the field for all those interested, and to serve as a stepping stone towards further relevant literature. To that end, the primary contributions of this paper are (1) a list of 48 wireless EEG devices along with a number of important—sometimes not easily obtained—features to enable their side-by-side comparison, and (2) a list of 110 high-impact journal publications making use of wireless EEG categorized by application and analyzed for device used, number of channels, sample size, and participant mobility. Together, these provide a basis for informed decision-making with respect to hardware and experimental precedents when considering new, wireless EEG devices and research. At the same time, starting in the next section, this paper provides some introductory and background material regarding EEG research itself and the individual characteristics of EEG devices.

## 2. Before adopting EEG

As mentioned in the introduction, wireless EEG systems have significantly lowered the threshold to record or otherwise incorporate EEG in research and development, and it can indeed be a valuable addition. However, it is important to note that these small, seemingly simple devices may appear to hide the actual complexity of EEG, just like the ease of application can hide the great care that must in fact be taken to obtain a meaningful signal. Even with all the advances in EEG hardware and methodology of the past decades, the adoption of EEG must be accompanied by a thorough understanding of the signal: its physiological origins, characteristics, limitations, and extraneous influences must always be taken into account. Luckily, even though the signal, at its core, is the same one that was recorded a century ago, our understanding of it has progressed as well.

For a brief introduction to EEG itself, the reader is referred to, e.g., Cohen's (2017) inviting introduction to the modality, or Biasiucci et al. (2019) primer. One important aspect to remember is the influence of various types of artefacts, or noise. The brain activity itself is only a tiny electromagnetic signal emanating from within a body—and situated in a world—full of other, much stronger sources of electromagnetism. The environment contains many electronic devices which can interfere with the recording, and which may themselves be neither stationary nor consistent in their electromagnetic spectrum. The user's movements can also greatly affect the signal, ranging from the large, overt movements that we can see and perhaps control for, to those we may not be able to easily detect, such as involuntary facial expressions (e.g., Tassinary and Cacioppo 1992). This is because the muscular activity itself, as well as the movements generated by that activity, affect the signal in different ways. Other sources of possible interference within the body are the eyes, the heart, and the skin. Dealing with artefacts is an essential part of both the design of any EEG experiment and the processing of EEG signals. Since many artefacts are largely caused by the user's movements or their motion through the environment, an increase in mobility often leads to an increase in artefacts of this sort. Artefacts can be particularly troublesome when they are systematically related to experimental conditions, for example when a comparison of walking versus sitting induces more motion artefacts in the former condition than in the latter. It is thus crucial to disentangle relevant brain activity from the artefactual activity for any meaningful analyses to be performed. Luck (2014, Ch. 6) provides an overview of the most common artifactual sources and some ways to mitigate them in the context of traditional research; Mihajlovic et al. (2015) provide a brief introduction to artefacts and a number of other considerations in the context of wireless EEG. Also see Gwin et al. (2010) and Jacobsen et al. (2021), for example, specifically for gait-related artefacts. A well-considered artefact handling pipeline is a must.

For further reading, this paper is part of a special issue on scientific practice in EEG research. In particular, Niso et al. (2022) provide an introduction and selected literature recommendations covering many aspects of EEG research, including considerations with respect to planning, data collection, and signal analysis. Aside from the above-mentioned sources, a further in-depth textbook dealing with EEG in general and EEG analyses in particular is presented by Cohen (2014), where chapter 2 specifically deals with a number of fundamental considerations. Also see Jackson and Bolger (2014) for a review focusing more on the physical and physiological principles of EEG and its measurement.

As we mentioned, a thorough understanding of the modality is a prerequisite for the successful use of EEG. This ultimately includes an understanding of the various characteristics of the hardware, to which we will turn in the next section, specifically related to our selection of wireless EEG systems.

## 3. Overview of wireless EEG hardware

To obtain a list of current wireless EEG hardware, we (1) performed the literature search described in the next section and extracted the devices used (excluding discontinued devices but including their successors, if available), and (2) performed a general Internet search for vendors of EEG equipment, and identified products on offer which fit the main criterion: an EEG acquisition device with support for a wireless transmission protocol.

For each of these devices, we then obtained the properties listed in Table 1. If these were not available from the official documentation, the manufacturers or officially licensed vendors were contacted directly with the request for information, and were informed that the purpose of this request was the inclusion of this information in the current publication. This resulted in some answers that could not be obtained, or could not be translated into a uniform value in the table. Those fields have been either left empty or interpreted to fit the table where possible.

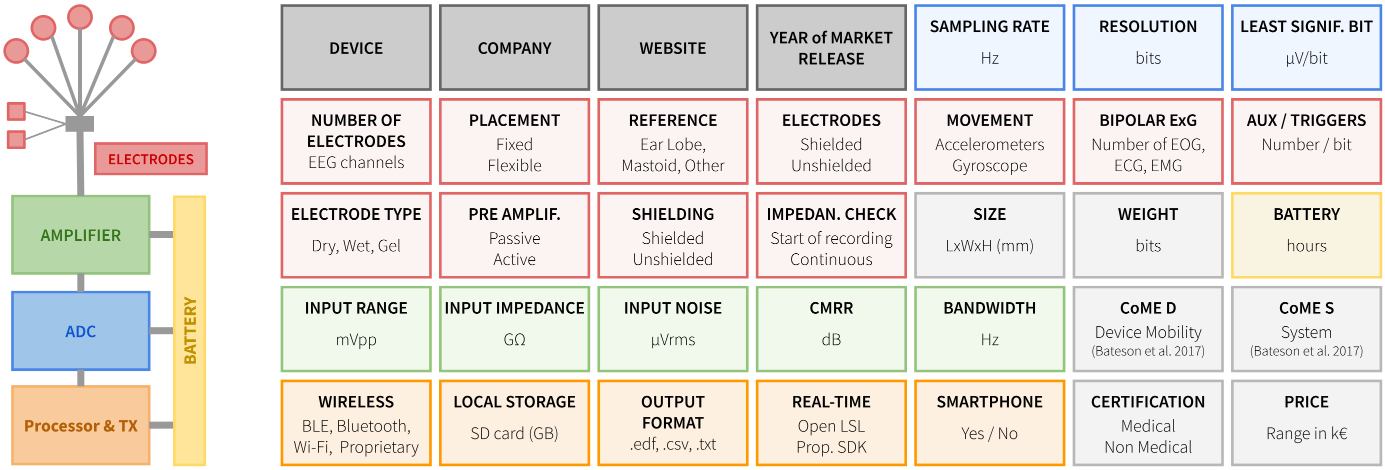
The remainder of this section will briefly discuss general considerations with respect to the different columns listed in Table 1, which have also been colour-coded and organized in Fig. 1. See also Fig. 3 for a visual summary of the devices listed along with some of their properties.

### 3.1. Company and device

The company and device name identify the device as it is on the market. As mentioned in the introduction, both traditional EEG companies and (relative) newcomers, even start-ups, compete in the wireless EEG market. The more established companies are more likely to offer a wider variety of products which may communicate well with the wireless EEG device, including e.g. software suites for analysis and additional hardware peripherals, potentially allowing the wireless EEG device to be embedded in a larger ecosystem for (neuro) physiological data acquisition. See Fig. 2 for an impression of the devices listed in Table 1.

### 3.2. Number and placement of EEG and reference channels

The number of EEG channels listed in the table refers to the effective number of EEG channels in the acquired data, i.e. excluding ground and reference electrodes. The number of EEG channels that can be measured can be an important consideration, depending heavily on the intended use of the system, but the primary, related concern should perhaps be one of *coverage*: how much, or what areas, of the scalp are covered by the available electrodes? Exploratory or fundamental research, or applications where data-driven methods (e.g. for artefact rejection or source localization) will be used, will generally benefit from increased head coverage, also meaning a certain minimum number of channels will be required. In traditional EEG research, where the concerns specific to portable systems can easily be ignored, a minimum of 32 channels is often used to provide broad scalp coverage. High-density EEG currently uses up to 256 channels. However, limited coverage can suffice for specific applications, where the relevant electrode sites are known. For research of the visual or motor cortices, for example, it can suffice to place a relatively small number of channels over the occipital or central sites, respectively. Using more channels may be tempting, and may be useful in specific cases even for local coverage, but more channels will also take longer to prepare, may be more intrusive, will require more storage



| | | | | | | |
|---|---|---|---|---|---|---|
| DEVICE | COMPANY | WEBSITE | YEAR of MARKET RELEASE | SAMPLING RATE<br>Hz | RESOLUTION<br>bits | LEAST SIGNIF. BIT<br>µV/bit |
| NUMBER OF ELECTRODES<br>EEG channels | PLACEMENT<br>Fixed<br>Flexible | REFERENCE<br>Ear Lobe, Mastoid, Other | ELECTRODES<br>Shielded<br>Unshielded | MOVEMENT<br>Accelerometers<br>Gyroscope | BIPOLAR ExG<br>Number of EOG, ECG, EMG | AUX / TRIGGERS<br>Number / bit |
| ELECTRODE TYPE<br>Dry, Wet, Gel | PRE AMPLIF.<br>Passive<br>Active | SHIELDING<br>Shielded<br>Unshielded | IMPEDAN. CHECK<br>Start of recording<br>Continuous | SIZE<br>LxWxH (mm) | WEIGHT<br>bits | BATTERY<br>hours |
| INPUT RANGE<br>mVpp | INPUT IMPEDANCE<br>GΩ | INPUT NOISE<br>µVrms | CMRR<br>dB | BANDWIDTH<br>Hz | CoME D<br>Device Mobility<br>(Bateson et al. 2017) | CoME S<br>System<br>(Bateson et al. 2017) |
| WIRELESS<br>BLE, Bluetooth, Wi-Fi, Proprietary | LOCAL STORAGE<br>SD card (GB) | OUTPUT FORMAT<br>.edf, .csv, .txt | REAL-TIME<br>Open LSL<br>Prop. SDK | SMARTPHONE<br>Yes / No | CERTIFICATION<br>Medical<br>Non Medical | PRICE<br>Range in k€ |

**Fig. 1. Schematic overview of the main characteristics of wireless EEG devices, specified in Table 1.** Characteristics are colour-coded with respect to the physical part of the device they relate to: electrodes (red), amplifier (green), analog-to-digital-converter (blue), processing and transmission (orange), battery (yellow), or the device as a whole (grey).

**Table 1. Specifications of wireless EEG devices.** Systems are sorted alphabetically by company name. Displayed characteristics include: device, company, website as of 2022 from which the data was taken, year of market release, number of EEG electrodes, EEG electrode placement (Fixed or Flexible), reference location (E: earlobe, M: mastoid, 2M: linked mastoids, Flex: multiple reference choices, otherwise 10–20 location), movement tracking accelerometers and gyroscopes, number of bipolar ExG and auxiliary channels (numbers in brackets indicate the ability to repurpose available EEG electrodes), availability and type of trigger ports, electrode type (i.e. Dry, Wet, Gel; Hybrid indicates that the same electrodes can be used in multiple ways), active pre-amplification or passive electrodes, shielded/unshielded electrodes, impedance monitoring capabilities (Start: possible before recording, Check: possible to check while recording, Continuous: monitored continuously, No: not possible), input signal range (mVpp), input impedance (GΩ), input noise ($\mu$Vrms), common mode rejection ratio CMRR (dB), amplifier bandwidth (Hz), sampling rate (in Hz), digital resolution (bit), least significant bit ($\mu$V/bit), size (mm) and weight (g), battery life (in hours), wireless protocol (i.e. Bluetooth, BLE, Wi-Fi, or ISM Proprietary at 2.4 GHz), local storage (size of local storage, or SD for SD card support, or No for no local storage), supported output formats, real-time streaming support (LSL: lab streaming layer compatible, SDK: software development kit available, additional information follows vendor specifications), smartphone EEG support (following vendor specifications), CoME D score for device mobility and CoME S score for system specifications according to Bateson et al. (2017); when information needed to calculate the score was missing, the lowest value was used, medical certification, and price range (k€) valid as of December 2022. A hyphen (-) indicates that the information could not be obtained.

| Device | Company | Year market release | Number of EEG electrodes | Electrode placement | Reference location | Accelerometer | Gyroscope | Bipolar ExG | Aux | Triggers | Electrode type | Electrode preamplification | Electrode shielding | Impedance check | Input range (mVpp) | Input impedance (GΩ) | Input noise (µVrms) | CMRR (dB) | Bandwidth (Hz) | Sampling Rate (Hz) | Resolution (bits) | Least significant bit (µV/bit) | Size (mm) | Weight (g) | Battery (h) | Wireless Protocol | Local storage / SD card | Output format | Real-time streaming | Smartphone EEG | CoME *D*: Device Mobility | CoME *S*: System | Medical certification | Price Range (k€) | Website |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **B-Alert X10** | Advanced Brain Monitoring | 2010 | 9 | Fixed | 2M | Yes | No | 1 | 0 | - | Gel | Passive | Unshielded | Start | 2 | 0.5 | 1.06 | 115 | 0.1-67 | 256 | 16 | 0.031 | 71x48x20 | 71 | 8 | Bluetooth | No | edf | SDK | Possible | 4 | 9 | No | 8-10 | advancedbrainmonitoring.com/products/b-alert-x-series |
| **B-Alert X24** | Advanced Brain Monitoring | 2012 | 20 | Fixed | 2M | Yes | No | 1 | 0 | - | Gel | Passive | Unshielded | Start | 2 | 0.5 | 1.06 | 115 | 0.1-67 | 256 | 16 | 0.031 | 71x48x20 | 71 | 8 | Bluetooth | No | edf | SDK | Possible | 4 | 9 | No | 12-15 | advancedbrainmonitoring.com/products/b-alert-x-series |
| **Stat X-Series X24** | Advanced Brain Monitoring | 2020 | 20 | Fixed | 2M | Yes | No | 1 | - | - | Gel | Passive | Unshielded | Start | 2 | 0.5 | 1.06 | 115 | 0.1-67 | 256 | 16 | 0.031 | 71x48x20 | 71 | 8 | Bluetooth | No | edf | SDK | Possible | 4 | 9 | Yes | 12-15 | advancedbrainmonitoring.com/products/stat-x-series-eeg |
| **eego mini 24** | ANT Neuro | 2022 | 24 | Flexible | CPz/Cz,M | Yes | No | 4 | 0 | Yes (2-bit) | Dry, Wet, Gel | Passive | Shielded | Gel:Start / Dry: Continuous | 1000-150 | 1 | 1 | 100 | 0-532 | 2048 | 24 | 0.009-0.060 | 115x90x20 | 100 | usb | WiFi | No | cnt, asc, eeg, edf | LSL/SDK | Yes | 4 | 14-12 | Yes | - | ant-neuro.com/products/eego_24 |
| **eego mini 8** | ANT Neuro | 2016 | 8 | Flexible | CPz/Cz,M | Yes | No | 0 | 0 | Yes (2-bit) | Dry, Wet, Gel | Passive | Shielded | Gel:Start / Dry: Continuous | 1000-150 | 1 | 1 | 100 | 0-532 | 2048 | 24 | 0.009-0.060 | 100x86x16 | 100 | usb | WiFi | No | cnt, asc, eeg, edf | LSL/SDK | Yes | 4 | 14-12 | Yes | - | ant-neuro.com/products/eego_8 |
| **eego sports** | ANT Neuro | 2015 | 128/64/32 | Flexible | CPz/Cz,M | Yes | No | 24 | (16) | Yes (8-bit) | Dry, Wet, Gel | Passive | Shielded | Gel:Start / Dry: Continuous | 1000-150 | 1 | 1 | 100 | 0-532 | 2048 | 24 | 0.009-0.060 | 205x160x22 | 500 | 5 | WiFi | No | cnt, asc, eeg, edf | LSL/SDK | Yes | 4 | 15-13 | Yes | - | ant-neuro.com/products/eego_sports |
| **Air** | Bitbrain | 2018 | 8 | Fixed | E | Yes | Yes | 0 | 1 | Yes | Dry | Passive | Shielded | Continuous | 200 | 50 | 0.7 | 100 | 0-40 | 256 | 24 | 0.012 | 210x165x55 | 212 | 8 | Bluetooth | SD | csv | LSL/SDK | In Beta | 4 | 10 | No | 5 | bitbrain.com/neurotechnology-products/dry-eeg/air |
| **Diadem** | Bitbrain | 2016 | 12 | Fixed | E | Yes | Yes | 0 | 1 | Yes | Dry | Passive | Shielded | Continuous | 200 | 50 | 0.7 | 100 | 0-40 | 256 | 24 | 0.012 | 210x165x110 | 307 | 8 | Bluetooth | SD | csv | LSL/SDK | In Beta | 4 | 10 | No | 13 | bitbrain.com/neurotechnology-products/dry-eeg/diadem |
| **Hero** | Bitbrain | 2022 | 9 | Fixed | E | Yes | Yes | 0 | 0 | No | Dry | Passive | Shielded | Continuous | 200 | 50 | 0.7 | 100 | 0-40 | 256 | 24 | 0.012 | 200x170x110 | 250 | 3 | Bluetooth | SD | csv | LSL/SDK | In Beta | 4 | 10 | No | 13 | bitbrain.com/neurotechnology-products/dry-eeg/hero |
| **Neuroheadband** | Bitbrain | 2023 | 5 | Fixed | E | Yes | Yes | 0 | 0 | No | Dry | Passive | Shielded | Continuous | 200 | 50 | 0.7 | 100 | 0-40 | 256 | 24 | 0.012 | 25x77x40 | 100 | 8 | BLE | No | csv | LSL/SDK | In Beta | 4 | 10 | On going | 2-4 | bitbrain.com |
| **Versatile EEG** | Bitbrain | 2017 | 64/32/16/8 | Flexible | E | Yes | Yes | 4/2/0/0 | 2/1/1/1 | Yes | Wet | Passive | Shielded | Continuous | 200 | 50 | 0.7 | 100 | 0-40/70 | 256 | 24 | 0.012 | 105x70x30 | 192/290/450 | 8 | Bluetooth | SD | csv | LSL/SDK | In Beta | 4 | 11 | No | 26/14/9/4 | bitbrain.com/neurotechnology-products/semi-dry-eeg/versatile-eeg |
| **LiveAmp** | Brain Products | 2015 | 64/32/16/8 | Flexible | Flex | Yes | No | 8 | 8 | Yes (8-/1-bit) | Dry, Wet, Gel | Active/Passive | Shielded | Start | 683 | 0.2 | 0.7 | 80 | 65/131/262 | 1000/500/250 | 24 | 0.041 | 83x51x14 | 60 | 4/24 | Prop | SD | eeg | LSL/SDK/TCP-IP | No | 3 | 15-10 | No | - | brainvision.com/products/liveamp-8-16-32 |
| **X.on** | Brain Products | 2022 | 7 | Fixed | E | Yes | - | 1 | 1 | In-app | Wet | Passive | Unshielded | Start | 625(BT5)/ 20 (BLE) | 0.4 | 1 | 75 | 0.1-131 | 500/250/125 | 24(BT5)/ 16(BLE) | 0.037/0.298 | 200x190x130 | 120 | 5 | BLE, BT5 | Phone | eeg | LSL | Yes | 4 | 11-7 | No | 2.5 | xon-eeg.com |
| **Mobile** | CGX (Cognionics) | 2021 | 128/72 | Flexible | - | Yes | No | 0 | 0 | Yes | Gel | Active | Unshielded | Continuous | 1666 | 1000 | 1 | 120 | 131 | 500 | 24 | 0.099 | 200x190x180 | 1000 | 10-4 | Bluetooth | SD | bdf, edf, lay, eeg, csv | LSL | No | 3 | 13 | No | 45-60 | cgxsystems.com/products |
| **Quick20r v2** | CGX (Cognionics) | 2021 | 21 | Fixed | E | Yes | No | 2 | - | Yes | Dry | Active | Shielded | Continuous | 1666 | 1000 | 1 | 120 | 131 | 500 | 24 | 0.099 | 200x190x180 | 596 | 8 | BLE | No | bdf, edf, lay, eeg, csv | LSL | In Beta | 4 | 12 | No | 20 | cgxsystems.com/products |
| **Quick32r** | CGX (Cognionics) | 2021 | 30 | Fixed | E | Yes | No | 2 | 0 | Yes | Dry | Active | Shielded | Continuous | 1666 | 1000 | 1 | 120 | 131 | 500 | 24 | 0.099 | 200x190x180 | 646 | 8 | BLE | No | bdf, edf, lay, eeg, csv | LSL | In Beta | 4 | 12 | No | 28 | cgxsystems.com/products |
| **Siesta Wireless** | Compumedics | 2001 | 32 | Flexible | Flex | - | - | 0 | 0 | - | Wet, Gel | Active | - | Start/Checked | 500-2 | 0.01 | 0.7 | 100 | 210 | 1000/100 | 16 | 0.031-7.6 | 140x76x38 | 300 | 24 | WiFi | SD | eeg, edf | - | - | 2 | 14-10 | Yes | - | compumedicsneuroscan.com/product/siesta-wireless-eeg- |
| **EPOC X** | Emotiv | - | 14 | Fixed | P3/P4/M | - | - | - | - | - | Wet | Passive | - | Continuous | 8 | - | 0.5/0.13 | - | 0.16-43 | 256/128 | 16/14 | 0.122-0.488 | 250x236x130 | 1000 | 12-6 | BLE, Bluetooth, Prop | No | csv, edf | - | Yes | 4 | 9-7 | No | <1 | emotiv.com/comparison |
| **EPOC-Flex** | Emotiv | - | 32 | Fixed | Flex/E | - | - | - | - | - | Wet, Gel | Passive | - | Continuous | 8 |  | 0.5 |  | 0.16-43 | 128 | 14 | 0.488 | 258x185x121 | 1000 | 9 | BLE, Prop | No | csv, edf | - | No | 3 | 8-7 | No | 1-2 | emotiv.com/comparison |
| **INSIGHT** | Emotiv | - | 5 | Fixed | M | - | - | 0 | 0 | - | Dry | Passive | - | Continuous | 8 | - | 0.5 | - | 0.5-43 | 128 | 16 | 0.122 | 212x212x123 | 1000 | 20 | BLE, Bluetooth | No | csv, edf | - | Yes | 4 | 8 | No | <0.5 | emotiv.com/comparison |
| **g.Nautilus MULTI-PURPOSE** | g.tec | 2014 | 32/16/8 | Flexible | E/M | Yes | No | (32/16/8) | (32/16/8) | Yes (8-bit) | Gel, Dry/Gel (hybrid) | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 500/250 | 24 | 0.022-0.272 | 78x60x26 | 110 | 10 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 12-10 | No | 5-36 | gtec.at/product/gnautilus-multipurpose |
| **g.Nautilus MULTI-PURPOSE** | g.tec | 2014 | 64 | Flexible | E/M | Yes | No | (32) | (32) | Yes (8-bit) | Gel, Dry/Gel (hybrid) | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 250 | 24 | 0.022-0.270 | 78x60x36 | 140 | 6 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 14-11 | No | 5-36 | gtec.at/product/gnautilus-multipurpose |
| **g.Nautilus PRO Flexible** | g.tec | - | 32/16/8 | Flexible | E/M | Yes | No | (32/16/8) | (32/16/8) | Yes (8-bit) | Gel, Dry/Gel (hybrid) | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 500/250 | 24 | 0.022-0.273 | 78x94x26 | 110 | 10 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 14-11 | Yes | 6.5-25 | gtec.at/product/g-nautilus-pro-flexible |
| **g.Nautilus RESEARCH** | g.tec | 2014 | 32/16/8 | Flexible | E/M | Yes | No | 0 | 0 | Yes (8-bit) | Dry, Gel | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 500/250 | 24 | 0.022-0.274 | 78x60x26 | 110 | 10 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 12-10 | No | 5-35 | gtec.at/product/gnautilus-research |
| **g.Nautilus RESEARCH** | g.tec | 2014 | 64 | Flexible | E/M | Yes | No | 0 | 0 | Yes (8-bit) | Dry, Gel | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 250 | 24 | 0.022-0.271 | 78x60x36 | 140 | 6 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 14-11 | No | 5-35 | gtec.at/product/gnautilus-research |
| **g.NautilusPRO** | g.tec | 2014 | 32/16/8 | Flexible | E/M | Yes | No | 0 | 0 | Yes (8-bit) | Dry, Gel | Active | Unshielded | Start/Checked | 4500-375 | 0.1 | 0.6 | 100/45 | 0-10230 | 500/250 | 24 | 0.022-0.275 | 78x60x26 | 110 | 10 | Prop | No | hdf5, mat, edf, gdf, csv | LSL | No | 3 | 14-11 | Yes | 6-20 | gtec.at/product/gnautilus-pro |
| **Unicorn Hybrid Black** | g.tec | 2019 | 8 | Flexible | M | Yes | Yes | 0 | 0 | No | Dry/Gel (hybrid) | Passive | Unshielded | No | 4500-375 | - | - | - | 0-10230 | 250 | 24 | 0.022-0.268 | - | - | 4 | Bluetooth | No | csv | LSL | Yes | 4 | 11-9 | No | <1 | unicorn-bi.com/brain-interface-technology |
| **Unicorn Naked BCI** | g.tec | - | 8 | Flexible | M | Yes | Yes | 0 | 0 | No | Dry/Gel (hybrid) | Passive | Unshielded | No | 4500-375 | - | - | - | 0-10230 | 250 | 24 | 0.022-0.269 | - | - | 4 | Bluetooth | No | csv | LSL | Yes | 4 | 11-9 | No | <1 | unicorn-bi.com/naked-bci |
| **MUSE 2** | InteraXon | 2018 | 4 | Fixed | FPz | Yes | Yes | 0 | 2 | No | Dry | Passive | Shielded | No | 2 | - | - | - | 100 | 256 | 12 | 0.488 | - | 39 | 5 | Bluetooth | No | csv, edf | LSL/SDK/OSC | Yes | 4 | 7 | No | <0.5 | choosemuse.com/muse-2 |
| **MUSE S** | InteraXon | 2021 | 4 | Fixed | FPz | Yes | Yes | 0 | 2 | No | Dry | Passive | Shielded | No | 2 | - | - | - | 100 | 256 | 12 | 0.488 | - | 41 | 10 | Bluetooth | No | csv, edf | LSL/SDK/OSC | Yes | 4 | 8 | No | <0.5 | choosemuse.com/muse-s |
| **Smarting MOBI** | mBrainTrain | 2014 | 24 | Flexible | FCz/Flex | No | Yes | 0 | 0 | - | Wet, Gel | Passive | Unshielded | Continuous | 100 | 0,5-1 | 1 | 140 | 0-250 | 500/250 | 24 | 0.006 | 81x52x12 | 60 | 4 | Bluetooth | No | bdf; xdf | LSL | No | 3 | 12-10 | No | - | mbraintrain.com/smarting-mobi |
| **Smarting PRO** | mBrainTrain | 2021 | 32 | Flexible | FCz/Flex | Yes | Yes | 8 | (8) | Yes (1-bit) | Wet, Gel | Passive | Unshielded | Continuous | 100 | 0.5-1 | 1 | 140 | 0-500 (1000 SDcard) | 1000/500/250 (2000 SDcard) | 24 | 0.006 | 84x52x9 | 65 | 10 | BT5 | SD | bdf; xdf | LSL | Yes | 4 | 14-11 | No | - | mbraintrain.com/pro-line-mobile-eeg |
| **Smarting PRO X** | mBrainTrain | 2022 | 64 | Fixed | FCz/Flex | Yes | Yes | 8 | (8) | Yes (16/8/1-bit) | Wet, Gel | Passive | Unshielded | Continuous | 100 | 0.5-1 | 1 | 140 | 0-500 (1000 SDcard) | 1000/500/250 (4000 SDcard) | 24 | 0.006 | 84x52x9 | 65 | 11 | BT5 | SD | bdf; xdf | LSL | Yes | 4 | 14-11 | No | - | mbraintrain.com/pro-line-mobile-eeg |
| **Smarting SLEEP** | mBrainTrain | 2017 | 24 | Flexible | FCz/Flex | No | Yes | 0 | 0 | - | Gel | Passive | Unshielded | Continuous | 100 | 0,5-1 | 1 | 140 | 0-250 | 500/250 | 24 | 0.006 | 150x65x17 | 115 | 15 | Bluetooth | No | bdf; xdf | LSL | No | 3 | 13-12 | No | - | mbraintrain.com/smarting-mobi |
| **Explore** | Mentalab | 2020 | 8/4 | Flexible | Flex | Yes | Yes | (8/4) | - | Yes | Dry, Gel | Passive | Unshielded | Start | 400 | 1 | 0.4 | 106 | 0-60 | 1000/500/250 | 24 | 0.024 | 40x40x20 | 27 | 12 | Bluetooth | 520MB | csv, edf | LSL/API/SDK | Java API | 4 | 14-12 | No | 4.5-6 | mentalab.com |
| **Explore+** | Mentalab | 2022 | 32/16/8 | Flexible | Flex | Yes | Yes | (32) | - | Yes | Dry, Gel | Passive | Unshielded | Start | 400 | 1 | 0.4 | 106 | 0-60 | 1000/500/250 (2000 offline) | 24 | 0.024 | 54x50x20/ 48x38x20 | 36/27 | 12-10 | Bluetooth | 4GB | csv, edf | LSL/API/SDK | Java API | 4 | 14-10 | No | 7-20 | mentalab.com |
| **NeXus-10 MKII** | Mind Media | - | 4 | Flexible | E/M | - | - | (4) | 4 | Yes | Gel | Passive | Shielded | - | 200 | 1 | 1 | 90 | - | 2048 | 24 | 0.012 | 140x120x45 | 540 | 24 | Bluetooth | SD | txt, mat, edf | SDK | No | 2 | 17 | Yes | - | mindmedia.com/en/products/nexus-10-mkii |
| **SmartBCI x24/x32** | MITSAR | - | 32/24 | Flexible | Flex | - | - | - | 4 | - | Dry, Gel | Active | - | Continuous | 1400 | - | - | - | 0-70(BT3)/ 0-150(BT5) | 500(BT5)/ 250 (BT3) | 24 | 0.083 | 65x55x18 | 70 | 24-20 | Bluetooth, BT5 | 32GB | - | - | - | 3 | 15-12 | Yes | - | mitsar-eeg.com/eeg-system-solutions/smartbci-wireless-eeg-family |
| **SmartBCI x64** | MITSAR | - | 64 | Flexible | Flex | - | - | - | - | - | Gel | - | - | Continuous | 1400 | - | - | - | 0-70(BT5)/ 0-500(onboard) | 250(BT5) (2000 onboard) | 24 | 0.083 | 120x75x25 | 200 | 24 | BT5 | 1TB | - | - | - | 3 | 13 | No | - | mitsar-eeg.com/eeg-system-solutions/smartbci-wireless-eeg-family |
| **Enobio** | Neuroelectrics | 2011 | 32/20/8 | Flexible | M | Yes | No | 0 | 0 | - | Dry, Gel | Passive | Ushielded | Continuous | 800 | 1 | 10-100 | 115 | 125 | 500 | 24 | 0.048 | 89x61x24 | 81/83/97 | 6 | WiFi | SD | asc, txt, edf | LSL/SDK | No | 3 | 12-10 | Yes | 4-24 | neuroelectrics.com/solutions/enobio |
| **Crown** | Neurosity | 2021 | 8 | Fixed | T7 | Yes | - | 0 | 0 | - | Dry | Active/Passive | Shielded | - | 2500 | 200 | 0.25 | 80 | 0-128 | 256 | 24 | 0.067 | 160x160x80 | 228 | 3 | BLE, WiFi | 8GB | csv, edf, txt, json | LSL/SDK/OSC | Yes | 5 | 11-10 | No | <1 | neurosity.co |
| **Cyton+Daisy** | OpenBCI | 2014 | 16/8 | Flexible | E | Yes | No | - | - | - | Dry, Wet, Gel | Active/Passive | Shielded | Start/Checked | 5000 | 0.5 | 0.35 | 110 | 150 | 250/125 | 24 | 0.298 | 61x61x30 | 60 | 8 | BLE | SD | txt, bdf | LSL/Serial/UDP/OSC | Yes | 4 | 13-9 | No | 1-2 | shop.openbci.com/products/cyton-daisy-biosensing-boards-16-channel |
| **Ganglion** | OpenBCI | 2016 | 4 | Flexible | E | Yes | No | - | - | - | Dry, Wet, Gel | Passive | Shielded | Start/Checked | 3000 | 0.1 | 0.05 | 106 | 150 | 200 | 24 | 0.179 | 61x61x30 | 30 | 8 | BLE | SD | txt, bdf | LSL/Serial/UDP/OSC | Yes | 4 | 12-10 | No | <1 | shop.openbci.com/products/ganglion-board |
| **DSI-24** | Wearable Sensing | 2009 | 21 | Fixed | Pz/E | Yes | No | 3 | 0 | Yes (8-bit) | Dry | Active | Shielded | Continuous | 20 | 47 | 1.06 | 120 | 0.003-150 | 600/300 | 16 | 0.305 | 480-620 | 600 | 24 | Bluetooth | Yes | csv, edf | LSL/TCP-IP/API | Android / iOS API | 4 | 12-11 | No | - | wearablesensing.com/products/dsi-series |
| **DSI-7** | Wearable Sensing | 2013 | 7 | Fixed | Pz/E | Yes | No | 0 | 0 | Yes (4-bit) | Dry | Active | Shielded | Continuous | 20 | 47 | 1.06 | 120 | 0.003-150 | 600/300 | 16 | 0.305 | 480-620 | 350 | 12-8 | Bluetooth | Yes | csv, edf | LSL/TCP-IP/API | Android / iOS API | 4 | 11-10 | No | - | wearablesensing.com/products/dsi-series |
| **DSI-7 Flex** | Wearable Sensing | 2013 | 7 | Flexible | - | Yes | No | 0 | 0 | Yes (4-bit) | Dry | Active | Shielded | Continuous | 20 | 47 | 1.06 | 120 | 0.003-150 | 600/300 | 16 | 0.305 | - | 200 | 12-8 | Bluetooth | No | csv, edf | LSL/TCP-IP/API | Android / iOS API | 4 | 11-10 | No | - | wearablesensing.com/products/dsi-series |
| **VR300** | Wearable Sensing | 2015 | 7 | Fixed | P4/E | Yes | No | 0 | 0 | Yes (4-bit) | Dry | Active | Shielded | Continuous | 20 | 47 | 1.06 | 120 | 0.003-150 | 600/300 | 16 | 0.305 | 520-620 | 400 | 12-8 | Bluetooth | No | csv, edf | LSL/TCP-IP/API | Android / iOS API | 4 | 11-10 | No | - | wearablesensing.com/products/dsi-series |
| **Zeto WR19** | Zeto | 2020 | 21 | Fixed | Cz/M/E | Yes | Yes | 1 | 0 | Yes (8-bit) | Dry | Active | Shielded | Continuous | 750 | 1000 | 1 | 115 | 0-125 | 500/250 | 24 | 0.045 | 272x214x143 | 680 | 6-5 | WiFi | No | edf | LSL/SDK | Cloud data view | 4 | 12 | Yes | - | zeto-inc.com |

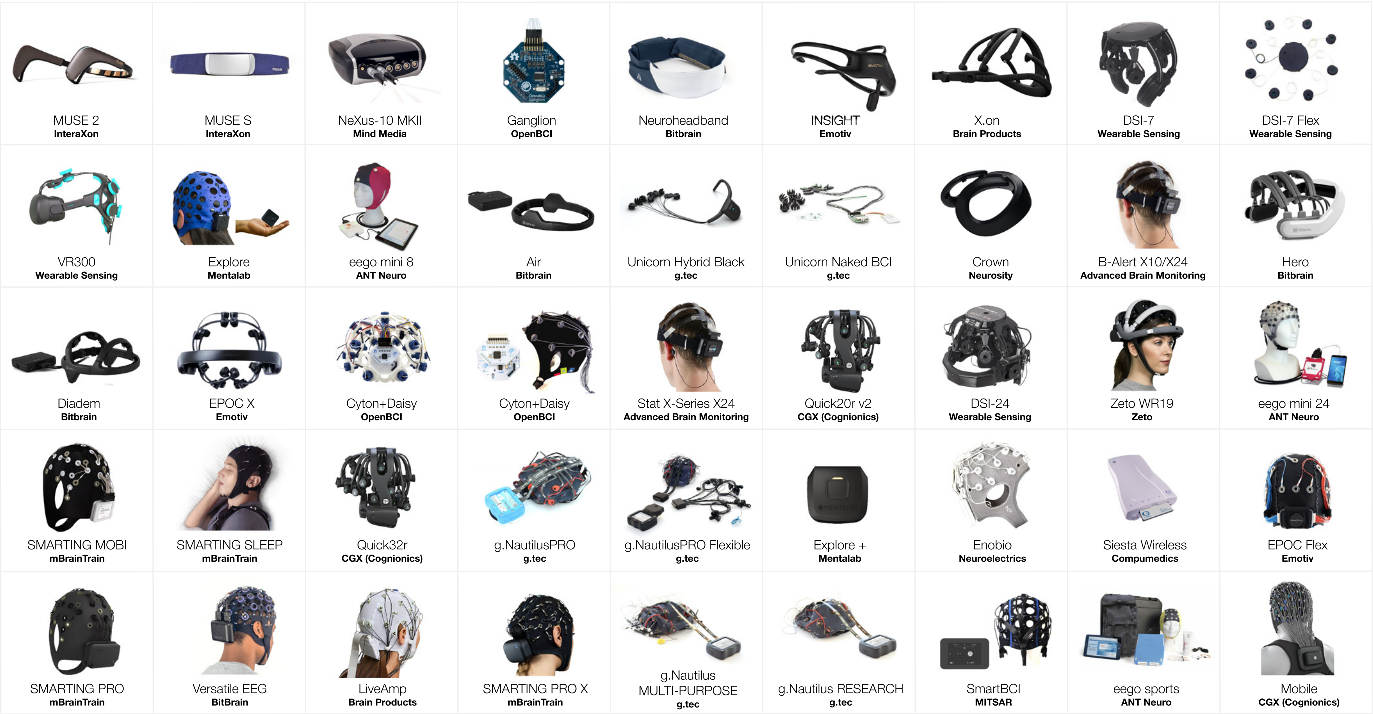


**Fig. 2. Images of reported wireless EEG systems.** Systems are sorted by number of EEG channels. Images were obtained with permission of manufacturers from their respective websites (see Table 1).

space and bandwidth, and may drain the battery faster. A first question to ask is thus: does my application need wide coverage of different sites, or can the relevant activity be recorded from a more spatially limited region?

A related deliberation relates to the fact that different applications may require different coverages. Some devices provide a fixed set of electrode locations. Here, a fixed design that provides maximum coverage may be appropriate, but not optimized, for a large variety of applications, whereas a design with limited coverage may be limited to specific use cases. An advantage of a fixed form factor is that the device as a whole helps to keep electrodes in place. It should be noted, however, that not all wireless EEG form factors can reach all regions of the scalp. When electrodes are embedded in a headband, for example, this necessarily excludes areas at the top of the head. Other devices offer (some) flexibility with respect to electrode locations, allowing you to reposition the electrodes depending on the application. Flexible designs generally make use of separate electrode caps that cover the head and allow electrodes to be attached, more or less freely, to that cap.

The reference electrode is a critical electrode because all other electrodes will be referenced against it (i.e., the reference activity will be subtracted from all other electrodes), as also mentioned in the primer cited earlier (Biasiucci et al., 2019). Note that, as mentioned above, some devices may allow (some) flexibility with respect to the electrode site, whereas others make this decision for you as part of their fixed form factor. The (default) reference location is given in Table 1 following the manufacturer's indications, often using the international standard 10-20 system, left/right ear (E), or mastoid (M).

From among the devices listed in Table 1, no general advice can be given with respect to the choice of reference, as the needs will depend on the application. Again, Luck (2014, Ch. 5) provides an excellent introduction to the relevant issues. Other than that, for comparability and reproducibility, it can be important to follow the standards set by others. Here, the experiments listed in the next section as well as traditional EEG literature can help. A final note specific to wireless EEG, however, is that the importance of the reference electrode is such that it may require special treatment, compared to the other electrodes. A good connection is crucial, and must be maintained throughout the recording. When movements can be expected to interfere with electrodes at certain sites, this must be taken into account when choosing a reference. The reference's importance is also why gel is sometimes used to increase the conductivity even when the other electrodes do not use gel (described further below).

### 3.3. Additional external and internal sensors

Aside from EEG, some devices allow additional electrodes to be connected to record data from different sources. This can be used for additional electrophysiological measures such as an electrooculogram (eye activity), electrocardiogram (heart), electromyogram (muscle), electrodermal skin activity, or respiration. Such measurements can be done in a bipolar fashion or using a unipolar auxiliary channel. The number of such available channels is listed in the table. Some devices may also have a trigger port to allow discrete event markers to be recorded, to synchronise the recordings with experimental events.

Finally, internal sensors are commonly recorded as if they were additional channels. Gyroscopes or accelerometers are often included to provide information about device movement. For head-mounted devices, this would directly translate into a measure of head movement. Table 1 contains separate counts for device gyroscopes and accelerometers.

### 3.4. Electrode type

The outer layer of the skin is a bad conductor of electricity. For this reason, so-called *gel-based* electrodes use an electrolyte gel that permeates the skin. The electrode itself, typically a small disk made of sintered silver/silver-chloride (Ag/AgCl), remains on the surface of the skin while the gel creates a highly conducive bridge to lower the impedance between skin and electrode. Gel also provides a buffer against mechanical movement of the electrodes. This gel is added manually during the preparation phase: the skin below each electrode is lightly cleaned, rubbed, and/or scratched, and gel is inserted using a syringe. While this provides the best signal quality from among the options listed in Table 1, it requires the most work, and, because the gel dries out over time, limits the maximum recording duration and leaves a residue that users will have to wash out.

The downsides of gel-based electrodes have spurred research into so-called *dry* electrodes, which do not require any additional substances, but instead use pressure to connect to the skin (Taheri et al., 1994). Dry sensors come in a wide variety of shapes and materials with many patented designs after more than 20 years of research (see Changkyun and Seo 2016, Lopez-Gordo et al. 2014, Chi et al. 2010, as well as Casson 2019 for systematic reviews). Their primary benefits are the faster and easier preparation (Di Flumeri et al., 2019), but this comes with some costs. For one, users may feel discomfort after some time, sometimes as low as 15 min, largely due to headaches caused by the electrodes' local pressure points (Zander et al., 2017; David Hairston et al., 2014). Dry electrodes also present higher noise levels, i.a. because noise is inversely proportional to the contact area which, depending on the design, can be quite small (e.g., Huigen et al. 2002). Moreover, dry sensors usually need higher low-frequency cut-offs, due to the noise contamination of the signal spectrum below 2 Hz and DC drifts due to sweating.

The main trade-off between gel and dry electrodes generally comes down to signal quality and comfort versus convenience. The large variety in dry electrode designs makes generalized statements difficult. While some reports state that new dry sensor systems can be used with comparable quality to traditional systems (Kam et al., 2019), and new shapes and materials have been proposed to minimize the noise on dry sensors (e.g., conductive polymers, graphene and textile; Casson 2019), especially in freely moving participants, dry electrodes are liable to produce a qualitatively worse signal (Mathewson et al., 2017). For various reasons, participants have reported to prefer some dry electrodes over gel-based alternatives in specific comparisons (Hinrichs et al., 2020). However, there are still very few published results that successfully use dry electrodes in mobile settings. Generally, primarily because of the mentioned issues of discomfort and noise, at the time of writing, most dry electrode systems are more suitable for short-term recordings in relatively stationary settings.

The so-called *wet* or *water-based* electrodes form a perhaps intermediate category. Wet electrodes generally consist of the same Ag/AgCl material used for gel-based electrodes, but are surrounded by a sponge-like material. They are prepared before application by immersing them in an ionic solution (e.g., saltwater), and allowing them to soak until saturated. The subsequent application on the scalp is then comparable to that of dry electrodes, while the ionic solution improves the conductivity and, by extension, the signal quality. One downside of these electrodes is that the maximum possible recording times will be shorter than for gel-based electrodes and can vary depending on conditions, as the ionic solution evaporates and the electrodes dry out.

Note that in most cases, especially for non-integrated systems, multiple electrode types are available, and a choice of system does not necessarily limit the choice of electrode type.

### *3.5. Active, passive, and shielded electrodes*

Nearby electrical equipment presents a substantial source of external noise in EEG devices: their electromagnetic activity is picked up by the electrode cables which essentially act as an antenna. One solution to this problem is to amplify the signal directly at the electrodes, before it is sent through the cables. To that end, so-called *active electrodes* have an additional ultra-low-noise pre-amplifier located inside the electrode. Some comparisons between passive and active amplification electrodes exist in stationary conditions (Shad et al., 2020; Laszlo et al., 2014) and during mobile tasks (Scanlon et al., 2021). In particular, the findings by Laszlo et al. (2014) suggest that active electrodes perform better with higher impedances, which are likely when using dry electrodes or when preparation time is short. However, despite the perceived advantages of active amplification, there is no general scenario in which passive electrodes can be said to always perform significantly worse, and much depends on further factors (Scanlon et al., 2021). For example, under optimal laboratory conditions with low electrode impedances, passive electrodes in fact provide cleaner data than active electrodes (Laszlo et al., 2014). With respect to signal quality, there is thus no single recommendation we can give in the context of wireless EEG. An important part of the decision will be the increased weight of the active electrodes compared to passive alternatives, reducing device and participant mobility. Where finances play a role, it should additionally be noted that active amplification significantly increases the cost of the electrodes.

Where preamplification is thus a measure that can be taken immediately at the electrode site, *shielding* refers to the protection of the signal as it travels through the cable, lowering the effects of environmental electromagnetic interference during transmission to the (main) amplifier. This is usually implemented using a layer of conductive metal surrounding the signal-carrying cable. Similar considerations as above apply, with shielded electrodes and electrode cables generally being heavier and more expensive (Jackson and Bolger, 2014).

### *3.6. Impedance check*

In order to evaluate the signal quality, devices provide a measure of impedance for each electrode. During preparation, this allows the experimenter or user to optimize the electrode's connection to the scalp. In some devices, this measurement cannot be performed during signal acquisition, meaning it can only be done before acquisition starts, and acquisition would have to be paused for any intermediate measures ('Start' in the table). Other devices provide the opportunity to check these values both at the start and on request during recording ('Start/Check'), while a final category allows impedance to be monitored continuously ('Continuous'). In such cases, the experimenter or user can keep an eye out for electrodes that lost contact during use. Where these quality control signals can be recorded along with the EEG, it can also be used to identify sections of noisy data for post hoc analyses. Such continuous quality metrics are especially useful using electrodes that are more susceptible to noise, and indeed dry-electrode devices are more likely to offer continuous impedance checks.

### *3.7. Amplifier characteristics*

An amplifier can be characterized, among other things, by its input range, gain, bandwidth, input impedance, and the common mode rejection ratio (CMRR). The input signal range refers to the input signal voltage (expressed in voltage peak-to-peak, Vpp) that the amplifier is able to accept as an input with a proper functioning. Since brain activity is typically in the range of μV or even mV, all systems shown in Table 1 will be able to properly amplify them without saturation. Special attention to the input range might be given in the presence of large artefacts (e.g. movements), which can produce an increase in the voltage of the signal resulting in amplifier saturation. Gain is the ratio between the output signal and the input signal (usually measured in dB) which reflects the degree of amplification of the system. This value is not often provided by vendors, since it is by itself not very informative as long as the amplifier is well designed for the specific input and output necessities, and thus it is not included in the table. The amplifier's bandwidth refers to the range of frequencies (expressed by $f_{max}$ and $f_{min}$) that it is able to amplify without distortion. The gain should be constant in the bandwidth in order to not alter the signal. As the amplifier will be specifically designed for the acquired brain signal and the subsequent systems in the processing of the device, we can assume that for all the devices in Table 1 both the gain and the bandwidth will always be sufficient. The input impedance (Ω) reflects the load seen by the signal when entering the amplifier. A high input impedance prevents the amplifier from draining current, improving its performance. Finally, the CMRR (dB) quantifies the ability of the device to reject signals that appear simultaneously and in-phase on both inputs of the amplifier. The higher CMRR the better the amplifier will perform against strong noise artefacts that are common to all electrodes, such as environmental electromagnetic interference.

### *3.8. Sampling rate*

Sampling rate refers to the number of samples that are digitally acquired per second, measured in Hertz (Hz). The Nyquist-Shannon theorem (Nyquist, 1928) states that for any periodic signal of a given frequency, a sampling rate higher than two times the frequency of the signal is needed to accurately detect its presence. In EEG, however, a larger margin is usually taken to allow for higher signal fidelity. Therefore, with the EEG activity of interest generally being up to around 50 Hz, sampling rates of 250 or 500 are common. Some recent wireless EEG devices have higher sampling rates, with several devices reaching over 1000 Hz (e.g. the Mind Media *NeXus-10 MKII* which can record up to 8000 Hz) enabling the study of high-frequency brain activity with wireless EEG systems, albeit at the cost of increased battery and storage requirements. Aside from studies that specifically require high sampling rates, for most applications of wireless EEG, a device's sampling rate itself is unlikely to be the deciding factor.

### *3.9. Digital resolution and least significant bit*

After sampling the analog brain activity, it is converted into a digital value by the analog-to-digital converter (ADC). The resolution of this converter denotes the number of finite values that the digital signal can span. As this number of values must be coded in binary, it is expressed as a number of bits. For example, a system with 10 bits resolution can encode an analog input in 1024 different levels ($2^{10} = 1024$), and a 24 bit resolution system can encode the same analog input in 16777216 different levels ($2^{24} = 16777216$). The higher the resolution, the better the digital signal can match the analog original.

The wireless EEG systems in Table 1 range from 12 to 24 bits. As Casson (2019) mentions, even the lower end of this range is sufficient for most EEG applications, although higher resolutions may still be preferred for fundamental research. Downsides of higher bit depths relate primarily to the wireless transmission: a higher resolution implies larger energy consumption in transmission and broader wireless transmission bandwidth. Compressing EEG data could be a possible solution in order to minimise data transmission, but due to the EEG signal's nature, this compression is extremely difficult (Zhang et al., 2013).

In addition to the digital resolution, Table 1 also includes the amplitude resolution of the least significant bit, LSB (in μV/bit), which represents the minimum input voltage level that produces a change in the output. This can be computed from the input range of the ADC: $\mathrm{mVpp}/2^{\mathrm{Resolution\ (bits)}}$. The lower this number is, the lower the quantization error, and therefore, the more accurate the recorded signal will be. Since this number is strongly dependent on other factors, unless there is a specific known requirement for a certain high resolution, it requires no further thought.

### *3.10. Size, weight, and battery life*

The size of the amplifier or device is listed in mm by descending dimensions (e.g., not the 'length', but simply the longest value is listed first), and the weight is listed in grams. Battery life indicates, in hours, the maximum duration of a recording on a single charge of the battery. The considerations here are obvious, where smaller and lighter will be better for most wireless cases as it increases device mobility, and a longer battery life increases participant mobility while providing more flexibility in terms of study design. Some studies that require long-term monitoring (e.g. overnight) may require battery life to be prioritized over other factors. Some systems allow hot-swapable batteries (e.g. Wearable Sensing *DSI-24)* or extending battery life with the use of a power bank, (e.g. Brain Products *LiveAmp)*, which allowing over 24 h of continuous recording. A perhaps expected correlation between size/weight and battery life does not emerge from this table. It should be noted, however, that some vendors do, and others do not include the sensors in the figures related to size and weight. Where sensors are attached separately, these numbers typically refer to the size and weight of the amplifier. Relatively speaking, the additional weight of the sensors are commonly negligible, especially for passive electrodes (see above). For integrated systems, the figures refer to the combination. With an average adult head length reaching roughly 20 cm, devices with a longest dimension over approximately 15 cm are generally integrated ones. The lightest device reported in Table 1 is the Mentablab *Explore*, an 8-channel amplifier weighing only 27 grams and particularly low size dimensions (40 × 40 × 20 mm).

### *3.11. Wireless protocol*

The defining factor of the devices listed in Table 1 is that they can transmit the acquired signal wirelessly. The protocol that is used for this transmission has some practical implications for the device's usage and mobility. The protocols that appear in Table 1 are Wi-Fi (IEEE 802.11), Bluetooth (IEEE 802.15.1), Bluetooth Low Energy (BLE, the Bluetooth 4.x releases with lower energy consumption), Bluetooth 5 (with more capabilities and compatible with both Bluetooth and BLE) and ISM Proprietary at 2.4GHz (usually based on IEEE 802.15.4 or IEEE 802.15.6). The main differences between these protocols relate to the transmission rate, range, and the frequency band in which they operate. Bluetooth and BLE have lower transmission rates (up to 2 Mbps) while Wi-Fi can have higher data rates (up to 2 Gbps). Nevertheless, transmission rate can be ignored for our purposes, as all protocols match the specifications of their respective devices to transmit the recorded signals with their respective specifications (e.g. number of channels, sampling rate, resolution).

The protocol's transmission range does have a major influence on the possible use cases. In technical terms, the limitation comes from the maximum ratio of transmitted power per unit of time allowed in the frequency bands, which is legally regulated. Also the type of antenna that the device incorporates influences the range: usually, Bluetooth transceivers have smaller antennas, while some Wi-Fi transceivers allow adding external antennas to increase transmission range. The typical effective transmission range for Bluetooth indoors is about 5–10 m, while for Wi-Fi this is about 10–20 m. If the receiving device is in the direct vicinity of the acquisition device, both protocols should provide equivalent performance. However, over longer distances, or when there may be no direct line of sight between transmitter and receiver, differences may become evident. This latter case can easily happen when the user's body itself blocks the line of sight, e.g. when the EEG device is carried at the back of the head but the receiver is located in front of them.

As for the frequency band, most of these wireless EEG interfaces are using the same 2.4 GHz frequency band. This is the most saturated unlicensed spectrum band in conventional environments, as these protocols have been adopted worldwide by handhelds (laptops, smartphones) and Internet-of-Things devices. As a result, a high number of wireless devices can lead to a degradation in the quality of communications. Wi-Fi protocol provides higher reliability (in terms of packets delivered) because it usually uses a higher transmission power (as a result, being more resistant against interferences and collisions) and also, because of the modulation used. On the other hand, energy consumption associated with communication is higher when using Wi-Fi.

Should the wireless connection be cut off for any period of time, some devices have the ability to store and process data locally, discussed next.

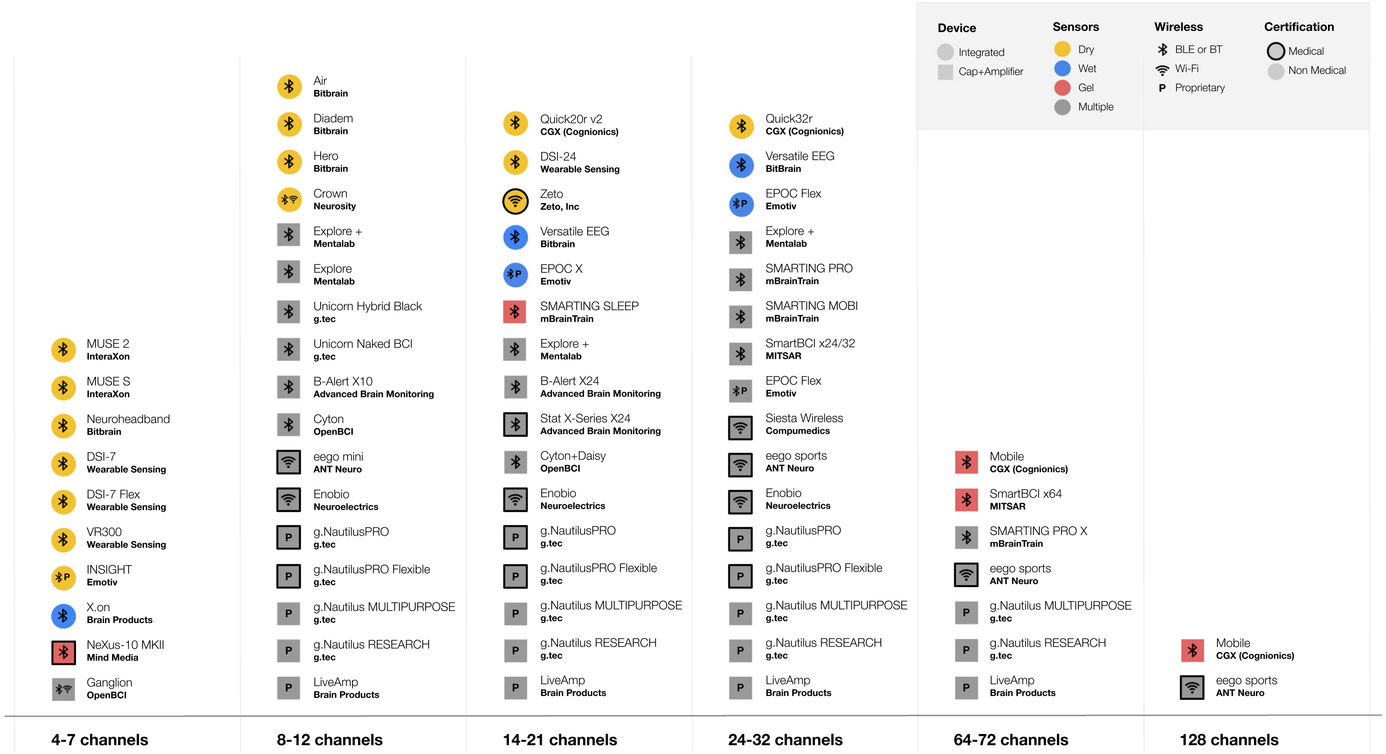


**Fig. 3. Visual summary of reported wireless EEG systems.** Wireless EEG systems are grouped by the number of channels, and each summary icon indicates the type of device: integrated (circle) or cap+amplifier (square), the type of available sensors: dry (yellow), wet (blue), dry (pink) or a multiple options (grey); the wireless protocol used: bluetooth or BLE, Wi-Fi, or ISM Proprietary at 2.4GHz; and the medical certification (black lined shape).

### 3.12. Data storage and output format

Some wireless EEG devices provide on-board signal recording capabilities. This means data can be stored on local, possibly removable, flash storage before or instead of wireless transmission. Thus, if the wireless signal is interrupted for any reason, it can be recovered and/or re-transmitted from a local copy, alleviating the risk of signal loss in unreliable wireless conditions.

The table also lists the file format in which the data can be stored. In some devices this is a fixed format, whereas more commonly, a choice is given through accompanying software. All of the devices listed in Table 1 support at least one open standard, and except from g.tec Unicorn and BitBrain systems that only export to .csv, all the other devices are able to export data in at least one of the recommended formats by the Brain Imaging Data Structure (BIDS) specification (i.e. European data format [.edf], Biosemi [.bdf] and BrainVision formats [.vhdr, .vmrk, .eeg]), facilitating the standardization of acquired brain data (Pernet et al., 2019; Niso et al., 2018; Holdgraf et al., 2019). Motion data will soon also be incorporated into BIDS, facilitating the standardization of recordings of movements coming tracking in virtual spaces or in physical motion capture systems with IMUs (Inertial Measurement Units). When this is done, prospective buyers for whom this is relevant may want to verify with the vendors that motion measurements, too, are organized according to the appropriate standard.

### 3.13. Real-time data access

Whereas local data storage is useful for the above-mentioned reasons, the primary purpose of the wireless protocol is usually to enable real-time remote acquisition of the data. Such access allows the device to be used for real-time cognitive monitoring, or for interactive applications where a connected device can use the brain activity as input and respond whenever specific mental states are detected—i.e., a brain-computer interface.

At the very least, real-time access is generally provided through some piece of software. Important for many cases, however, are the additional ways in which this data may be accessed and integrated into larger, custom processing pipelines. This is generally made possible through a separate software development kit (SDK), or through compatibility with open standards. In this latter category, the Lab Streaming Layer (LSL) has recently established itself as the main standard. LSL is a software framework that provides functionality to transmit and receive data over a local network, automatically handling data formatting, networking, synchronization, and real-time (or buffered) access. Devices from Table 1 that explicitly support LSL are directly compatible with a large ecosystem of both open-source and proprietary applications. When real-time access is provided through an SDK or through other open standards, this generally means that some additional programming is required before the device can be included in an existing experimental set-up (or to make the device LSL-compatible). This option may also be dependent on licensing agreements, potentially increasing the cost of operation. This also applies to devices that exclusively use proprietary software to access the data. In this latter case, embedding the device in existing set-ups may be difficult or even impossible.

### 3.14. Categorization of mobile EEG (CoME) score

Bateson et al. (2017) introduced the *Categorization of Mobile EEG* (CoME) scheme to provide a quantitative method for the categorization of different EEG systems, or different ways in which EEG systems are used, based on selected parameters. The CoME scheme provides three separate scores: a device mobility score, a participant mobility score, and a system specification score. Additionally, the full CoME score mentions the number of channels, which we already discussed above.

The device mobility score (CoME *D*) reflects where and how the EEG device is positioned, effectively representing the amount to which the participant is free from physical restrictions as a result of the device. The minimum score of 0 indicates a traditional, tethered system, while the maximum score of 5 refers to a fully head-mounted device with no additional equipment needed—not even to wirelessly receive the data.

The system specification score (CoME S) ranges from 4 to 20, and sums together four separate characteristics, each scored between 1 and 5. These four characteristics are *electrode type* (1 being passive, unshielded, dry electrodes, and 5 being active, shielded, gel electrodes; see above), *bit resolution* (starting at 14 bit for a score of 1, up to more than 24 bit for 5), *sampling rate* (from approx. 128 to more than 1000 Hz), and *battery life* (from *no battery* up to more than 24 h).

The participant mobility score, finally, reflects the activity of the wearer, ranging from lying, sitting, or standing still (0) to unconstrained sports (5).

Note that these scores are, in most cases, not fixed for a single EEG system: the same device can be positioned differently depending on the situational requirements, many devices allow for a selection of different sampling rates, electrodes, et cetera, with accordingly variable battery life, and even the most mobile system can still be used by a seated person. Still, we have attempted to score the devices in Table 1 with respect to the device mobility and system specification scores. For system specifications, we mention the highest possible score that the device theoretically supports. The same applies to device mobility, with the added note that we assume there is a need for real-time processing of the data. That is, mere on-device, offline recording capabilities do not satisfy the requirement for a score of 5 that no additional equipment is needed. The participant mobility score cannot meaningfully be determined for a device in isolation. This score, therefore, is not considered here, but used in the next section's literature review.

### 3.15. Medical certification

Use of devices in a clinical or medical context is only allowed when those devices have received the appropriate certifications. Appropriately certified devices would, for instance, have been approved by the Food and Drug Administration (FDA) in the United States, or the European Medicines Agency (EMA) in the European Union. While the presence or absence of such a certification makes no functional difference for non-medical use cases, including academic research, this certification is a requirement for clinical research, and has thus been included in Table 1.

### 3.16. Price range

Price is a very dynamic characteristic. To the extent that the manufacturers or vendors agreed to supply this information, it has been mentioned in Table 1 valid as of December 2022. Commonly, a range is given, reflecting the many customization features that can affect it. It is worth noting that in general, with few exceptions (e.g. OpenBCI, Emotiv, which are more consumer-grade systems), it is rare to find public prices available online, and only direct requests for a specific quote can provide an estimate. As a general rule of thumb, the price of wireless EEG systems seems directly related to the number of channels. Therefore, a careful selection of the number of electrodes (and their placement) is advisable prior to the acquisition of a new device.

## 4. Wireless EEG literature

This section provides a survey of published work that has made use of wireless EEG. The search for available literature using wireless EEG was performed in PubMed searching for 'EEG', 'electroencephalography', or 'electroencephalogram' occurring together with 'wireless', 'mobile', 'portable', 'wearable', or 'ambulatory' in the title or abstract, while excluding results that refer to animal studies. The search was performed in March 2022 and included search results up to and including all of 2021. For a closer look at a manageable but representative sample of impactful research, we retained only publications that were published in journals and were cited, on average, at least 10 times per year. Total citations were assessed using LISC (Donoghue, 2019) and averaged over the years since the article was published. Because we are primarily interested in the applications of wireless EEG, we furthermore manually removed publications that were reviews, methodological approaches or hardware designs without any experimental data. We further removed studies where the EEG system details were not reported. Finally, we extracted the general topic of the study, the device used, the number of channels, the number of participants, and determined the CoME participant mobility score described above. For further details of the literature review approach, see the flow diagram following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) in Fig. 4.

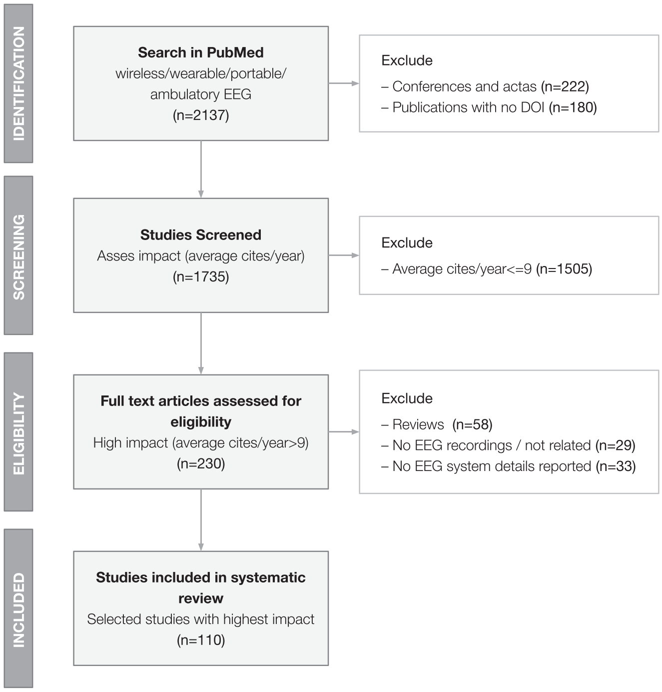


**Fig. 4.** Flow diagram for literature search, screening and inclusion process.

### 4.1. Overview

A total of 2137 papers were returned by the initial search result. The oldest result is from 1975, and describes a 4-channel 24 h cassette recorder for long-term EEG monitoring of ambulatory patients developed at the Montreal Neurological Institute (Ives and Woods, 1975). Since then, as Fig. 5a shows, the number of studies using wireless EEG systems has increased rapidly—but primarily so over the past ten years, and presently peaking in the most recent year. This figure represents the results of the initial search without further pruning.

Our selected sample includes 110 publications, which are referenced in Table 2. We can see that the number of participants in the analyzed wireless EEG studies is generally between 10 and 20, with a median of 18 (see Fig. 5b). However, a relatively large number of publications used a small sample, with 25 publications having fewer than 10 participants. In our sample, this appears to be a result of the relative novelty of these devices, where some studies are explorative feasibility studies proposing new designs or algorithms; however, all categories of applications contained examples of both larger and smaller samples. See Button et al. (2013) for a critique of sample sizes in neuroimaging research, which, as we can see, clearly applies to the wireless EEG subfield as well. The other extreme end of the scale is held by a large-scale study by Hashemi et al. (2016) which included 6029 participants to characterise EEG measures through adulthood using a 4-channel Muse device (excluded from the figure as an outlier for visualization purposes).

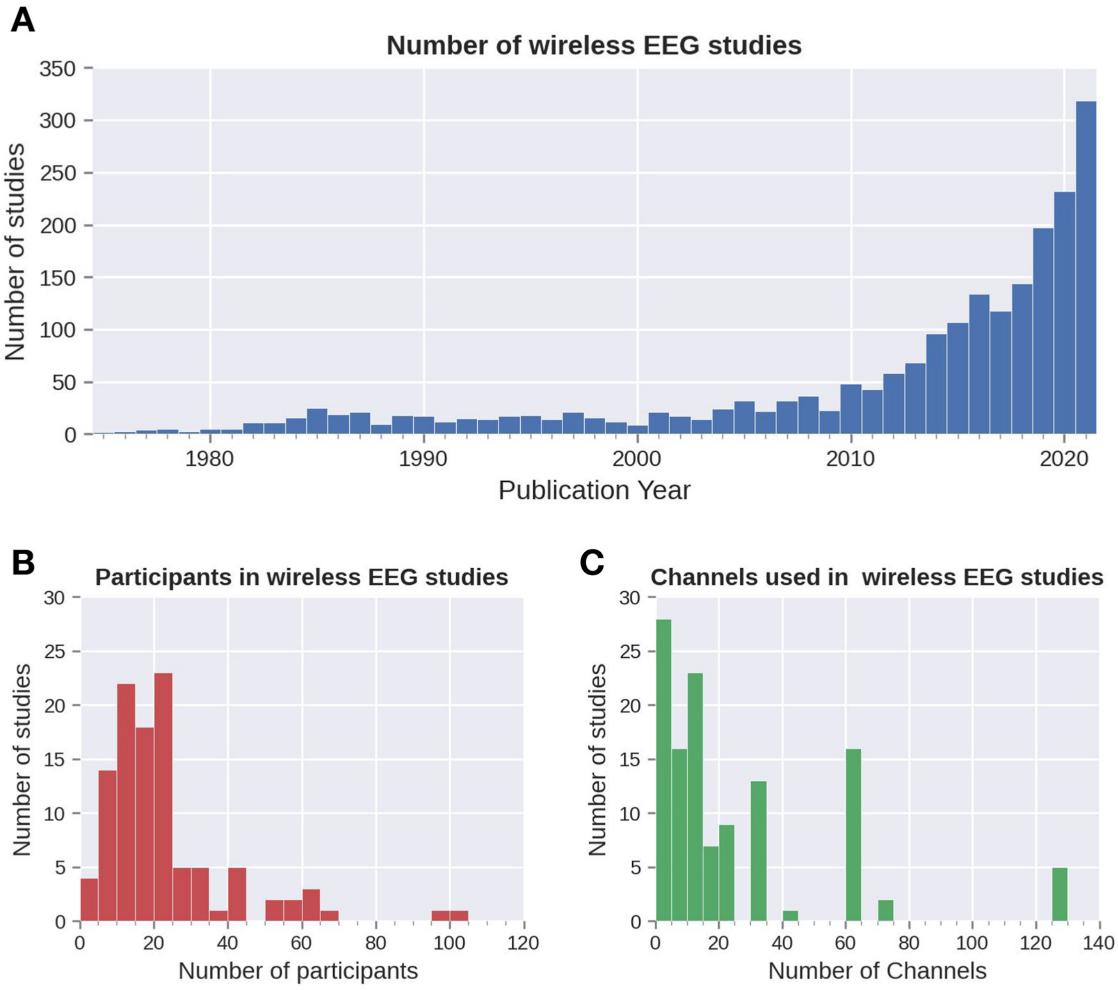


**Fig. 5. Overview of reviewed wireless EEG literature.** (A) number of studies using wireless EEG systems between 1975 and 2021 ($n = 2109$ out of the 2137 selected studies); (B) number of participants in the analyzed wireless EEG studies ($n = 110$); (C) number of channels reported ($n = 110$).

Fig. 5c shows the number of channels reported, and shows probably-familiar peaks at the powers of 2: 8, 16, 32, et cetera. The median number of channels is 14. To the left of the median, we see that here, too, a relatively large amount of studies used significantly fewer channels, with 37 publications using fewer than eight channels, and 11 publications reporting only one single channel. In part, this reflects the availability of devices, with e.g. the single-channel Neurosky *Mindwave* having been used in some of these publications, but it also goes hand in hand with one of the main reasons for adopting wireless EEG more generally: the wish for miniaturization and ease of use. In the list of 110 publications, one each reported using 157, 248, 256, and 264 channels, which have been excluded as outliers from the figures; furthermore, they primarily used stationary EEG devices in a mobile setting.

Fig. 6 illustrates which wireless EEG systems were used in these papers. Note that, as Bleichner and Debener (2017) also explained, 'mobile' EEG studies may still be performed using stationary, non-wireless devices. These were therefore removed for the illustration in Fig. 6. Fur-

**Table 2**
References of the 110 selected papers, organized by field of application.

| | |
|---|---|
| Clinical conditions | Chez et al., 2006; Malcolm et al., 2015; Lucey et al., 2016; Grønli et al., 2016; López-Larraz et al., 2016; Gu et al., 2017; Levendowski et al., 2017; Neale et al., 2017; Simons et al., 2018; Debellemaniere et al., 2018; Calabrò et al., 2018; Dres et al., 2019; Shustak et al., 2019; Mikkelsen et al., 2019; Ding et al., 2019; Jebelli et al., 2019; Ahn et al., 2019; Vandecasteele et al., 2020; Arnal et al., 2020; Nakamura et al., 2020; Martins et al., 2020; Cicalese et al., 2020; Clarke et al., 2021 |
| Cognitive monitoring | Holm et al., 2009; Gramann et al., 2010; Liao et al., 2012; Liu et al., 2013; Lin et al., 2014; De Sanctis et al., 2014; Aspinall et al., 2015; Mirkovic et al., 2016; Hashemi et al., 2016; Beurskens et al., 2016; Bradford et al., 2016; Zink et al., 2016; Leminen et al., 2017; Morales et al., 2017; Zhang et al., 2017; Poulsen et al., 2017; So et al., 2017; Banaei et al., 2017; Al-Barrak et al., 2017; Dikker et al., 2017; Katsigiannis and Ramzan, 2018; Marín-Morales et al., 2018; Athavipach et al., 2019; Gonzalez Viejo et al., 2019; Golnar-Nik et al., 2019; Ziegler et al., 2019; Dehais et al., 2019; Blanco et al., 2019; Solis-Escalante et al., 2019; Djebbara et al., 2019; Reiser et al., 2019; Piñeyro Salvidegoitia et al., 2019; Ladouce et al., 2019; Bevilacqua et al., 2019; Nordin et al., 2019; Scanlon et al., 2019; Fronso et al., 2019; Narayanan and Bertrand, 2020; Raheel et al., 2020; Zhang et al., 2020; Packheiser et al., 2020; Nordin et al., 2020; Lin et al., 2020; Topalovic et al., 2020; Bigliassi et al., 2020; Haar and Faisal, 2020; Mustile et al., 2021; Hölle et al., 2021 |
| Control and communication | Lin et al., 2010; De Vos et al., 2014; Ma et al., 2015; Luu et al., 2016; Kwak et al., 2017; Artoni et al., 2017; Chen et al., 2018; Zhang et al., 2019; Si-Mohammed et al., 2020; Shao et al., 2020; Tortora et al., 2020 |
| Methodological approaches | Chi et al., 2012; Badcock et al., 2013; De Vos et al., 2014b; David Hairston et al., 2014; Bleichner et al., 2015; Mikkelsen et al., 2015; Debener et al., 2015; Mullen et al., 2015; Snyder et al., 2015; Rogers et al., 2016; Nathan and Contreras-Vidal, 2015; Kilicarslan et al., 2016; Oliveira et al., 2016; Melnik et al., 2017; Krigolson et al., 2017; La et al., 2018; Radüntz, 2018; Kim et al., 2018; Kassab et al., 2018; Kam et al., 2019; Blum et al., 2019; Titgemeyer et al., 2020; Hinrichs et al., 2020; Li et al., 2020; Klug and Gramann, 2021; Reiser et al., 2021 |

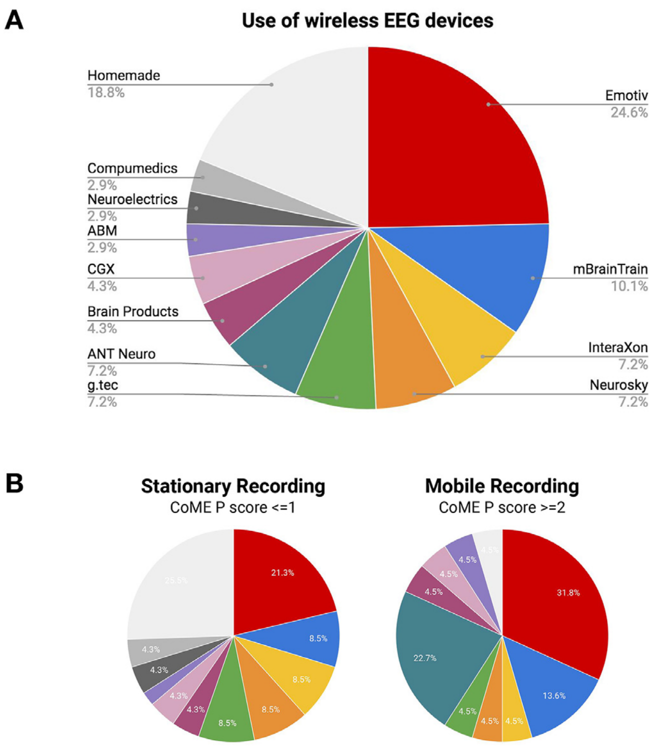


**Fig. 6. Distribution of wireless EEG devices used in the analyzed studies. (A)** For all studies: Emotiv 25%, Homemade 19%, mBrainTrain 10%, Interaxon 7%, Neurosky 7%, g.tec 7%, ANT Neuro 7%, Brain Products 4%, CGX 4%, Advanced Brain Monitoring (ABM) 3%, Neuroelectrics 3%, Compumedics 3% ($n = 69$). B) For studies where the CoME participant mobility score described in Bateson et al. (2017) is $P < = 1$ (left) and $P < = 2$ (right).

thermore, since many papers used now-discontinued devices, they are represented by manufacturer, rather than by model name. Devices that were not wireless, have no present-day successor, and occurred only once in the literature search are also not included, for a total of 69 papers represented in this figure.

From the included papers, 24.6% used an Emotiv *EPOC* system, and 10.1% a device by mBrainTrain (often in conjunction with cEEGrid, a type of non obtrusive, behind-the-ear electrodes; Debener et al., 2015); third place is shared equally among InteraXon (*Muse* family), Neurosky, g.tec, and ANT Neuro. The remainder is divided among 5 further manufacturers: Brain Products, ABM, Neuroelectrics, Compumedics, and CGX (formerly Cognionics). We point out that this is exclusively a measure of prevalence in our current selection, and that the popularity of any one device is likely to be influenced by a number of factors, including the time on the market and price, with Emotiv providing one of the first commercially available wireless EEG devices. Roughly as prevalent as the top branded device is the category of ‘home-made’ devices: devices that were either fully or partially constructed by the researchers themselves. A possible implication is that, on the one hand, off-the-shelf devices may not fulfil the many divergent requirements placed upon wireless EEG devices for different applications, while, on the other hand, research is active and ongoing into finding new and improved wireless EEG solutions.

Because the focus of this paper is on wireless EEG, the main purpose and benefit of which, as we mentioned, is the allowed participant mobility, we specifically focus here on papers with a CoME participant mobility score of at least 2. This is the case for 43 papers, or 39%. Fig. 6, bottom, illustrates the different distributions of these systems for essentially non-mobile studies ($P$ of 0 or 1), and mobile studies ($P >= 2$). We see that the category of ‘homemade’ devices, which are by and large intended to test new hardware designs, are in fact rarely tested using mobile participants. A notable difference is also given by ANT Neuro’s systems apparently being used primarily with mobile participants: no paper in the current selection used such a system for stationary participants.

### 4.2. Fields of application

The analyzed papers broadly fall into four identified categories: *cognitive monitoring, clinical conditions, communication and control*, and *methodological approaches*. These emerged from more specific topics or subfields attributed to each of the papers.

As illustrated in Fig. 7a, most studies investigated or employed cognitive monitoring, with 44.1% falling in this category. Clinical applications represented the second-largest group with 24.3% of papers, methodological approaches represented 21.6%, and communication and control 9.9%. Fig. 7b shows this in more detail, including the main identified subfield topics.

Fig. 7d groups the papers by the CoME participant mobility score mentioned in the previous section (Bateson et al., 2017). 40% of papers scored 1, meaning participants were ‘lying, sitting, or standing with localized movement’ such as button pressing. 21% scored 0, meaning there was not even any localized movement. Mobility proper starts at a score of 2, with constrained walking/cycling (19% of papers), and 19% achieve a score of 3, where walking/cycling is unconstrained. More involved activities, represented by scores 4 were used by only 3% and none of the papers scored 5.

Fig. 7c. illustrates the different distributions of the identified fields separately for non-mobile and mobile studies. The main, clearly observable difference here is that cognitive monitoring appears much more popular with increased mobility, whereas clinical applications are largely performed in non-mobile settings. Indeed, in mobile settings, more than half of all studies—even more than two thirds when considering only real-life applications and removing methodological research—make use of the technology to perform some form of cognitive monitoring.

In the following subsections, the three categories that refer to real-life applications will be discussed in more detail. This excludes the methodological investigations, which for example used wireless EEG for the purpose of hardware comparisons, artefact correction methods, validation studies or new system design proposals. We will primarily focus on studies with significant participant mobility, but as we will see, in a world where many activities are done in a seated position, the envisioned use cases are generally not limited to active scenarios.

#### 4.2.1. Cognitive monitoring

Cognitive monitoring here refers to the use of neurotechnology to, usually in a continuous and real-time fashion, obtain a measure or index of specific mental activity, such as preferences, emotions, or workload, to name just a few examples. When this is done interactively, i.e., when a device adapts or responds to the measured mental states in real time, this may also be referred to as *passive* BCI (Zander and Kothe, 2011; Krol et al., 2018) or *neuroadaptive* technology (Zander et al., 2016), but for our current purposes, we include this in the broader category of cognitive monitoring. This is the most common application of wireless EEG in the analyzed literature, with a total of 44% of all 110 papers in this category, 60% of all mobile papers, and even 73% when excluding methodological papers.

As for specific mental states to be detected using wireless EEG, ‘attention’ has received the most interest in the current sample. For example, Scanlon et al. (2019) used a 15-channel Brain Products *V-amp* to record an auditory oddball task in 12 cycling participants, measuring P300 responses as an index of attention. Gramann et al. (2010) used a visual oddball paradigm to compare attention-related indices during standing, walking, and running on a treadmill. Applications of attention-related cognitive monitoring have largely been sought in the educational domain (e.g. Bevilacqua et al. 2019, Dikker et al. 2017, Poulsen et al. 2017). Also automotive contexts form another popu-

**Fig. 7. Wireless EEG fields of application.** (A) Fields of application of wireless EEG devices in the analyzed studies: cognitive monitoring 44% (purple), clinical conditions 24% (orange), communication and control 10% (blue) and methodological approaches 21% (grey), ($n$ = 110). (B) Number of studies in each of the subfields applications with occurrence > 1: cognitive monitoring (purple), clinical conditions (orange) and communication and control (blue) and methodological approaches (grey). (C) Fields of application of wireless EEG devices in the analyzed studies where the CoME participant mobility score described in (Bateson et al., 2017) is $P <= 1$ (left) and $P <= 2$ (right). (D) Distribution of the fields of application of the analyzed studies for each CoME participant mobility score from 0 to 5.

lar field for attention-related cognitive monitoring (Lee et al., 2014; Lin et al., 2014; Zhang et al., 2017). In these two contexts, however, participant mobility according to the CoME score is in effect 1 as studying and driving are generally seated activities.

Another popular field of investigation, which does make clearer use of participant mobility, focuses on people's emotions and perceptions of the real world around them. For example, Banaei et al. (2017) used a 128-channel Brain Products *BrainAmp*, made wireless using the discontinued *MOVE* system, to investigate perceptions and experiences in various architectural spaces experienced in virtual reality. Similar studies have been performed in outdoor or urban areas. For example, Neale et al. (2017) used a 14-channel Emotiv *EPOC* with 95 senior participants. They used the device's accompanying commercial suite's indices for engagement, excitement, frustration, and meditation to look for significant differences while the participants were exploring different outdoors areas. They acknowledge that they cannot properly scrutinise these proprietary metrics, but report some significant differences.

Other targeted mental states are emotions, memory, and cognitive responses related to auditory presentation, such as attention to a specific speaker (Mirkovic et al., 2016) or responses to target sounds using auditory oddball paradigms (De Vos et al., 2014; Debener et al., 2012b; Ladouce et al., 2019). Neuromarketing is another category, where a variety of cognitive states may be used to detect consumer interests with respect to different products, including, in our sample, mobile phone brands (Golnar-Nik et al., 2019) and beer (Neale et al., 2017).

Cognitive monitoring allows real-life, everyday situations to be enhanced by technology that can assess and respond to information concerning human mental states. In the above example, a classroom teacher may be notified by neurotechnology when the students lost the thread of the teacher's explanation, without any student needing to explicitly communicate this. Similarly, a driver's drowsiness may be automatically detected and acted upon by an autonomous vehicle, avoiding potential catastrophe. And as most people today carry technology with them wherever they go, a smartphone that e.g. detects how some regions of the city evoke more positive emotions in us may in the future adapt its navigation suggestions to follow specific, pleasing routes, or conversely, use these methods to avoid locations with stressful traffic. As these examples show, most envisioned applications of such neuroadaptive technology would not practically be possible without wireless EEG.

### 4.2.2. Clinical conditions

EEG has always seen clinical interest, primarily for diagnostic purposes, and this is no different for wireless EEG, with 24.3% of all 110 analyzed papers in this category. This number drops significantly to 11.6%, however, when considering only situations in which participants are mobile (14.3% excluding methodological papers). This may indicate that in clinical settings, other considerations than participant mobility take precedence to opt for wireless EEG devices. The mobile conditions in our sample involve exoskeletons, age-related research, and long-term monitoring of pathological conditions.

For example, Chez et al. (2006) recorded EEG of 889 participants using a discontinued DigiTrace device, for a total of 24 h each, thus requiring some freedom of mobility of the patients. They sought to assess the frequency of EEG abnormalities in patients with autism spectrum disorders. In less mobile situations, clinical conditions often focus on phases of sleep. For example, Shustak et al. (2019) presented a 4-channel custom 'temporary-tattoo EEG' device, which contains thin, printed electrodes applied directly onto the skip without gel, for unobtrusive sleep monitoring at home, and reported 'clear differentiation of sleep stages' based on data recorded during either short naps (2 h) or longer night sleeps (6 h) of nine participants. For a systematic review of the accuracy of wearable devices for estimating sleep onset, see Scott et al. (2020). Dementia, stress, depression, and migraines are other conditions that were monitored using wireless EEG in our sample.

Exoskeletons are machines that support part or all of the body, for example in situations where a person's natural strength or stamina are insufficient. They can furthermore be used for rehabilitation when motor functions are impaired, e.g. after a stroke. For example, López-Larraz et al. (2016) used an unspecified 32-channel mobile EEG system from g.tec in order to detect a stroke patient's movement intentions in real time, allowing the exoskeleton to perform supportive movements.

While many clinical studies are performed bedside or in other stationary conditions, as is evident e.g. from Fig. 7d, wireless EEG allows freedom of mobility during the long-term monitoring that is often required to detect clinical symptoms in the EEG. This opens new doors as longer monitoring becomes possible, as well monitoring under different, specifically real-life conditions. For rehabilitation, where participant mobility is in fact the goal of the therapy, wireless EEG similarly allows new avenues to be explored.

### 4.2.3. *Communication and control*

Wireless EEG, especially direct-to-consumer, commercial devices, is often used as an input modality to replace or supplement e.g. a keyboard or a mouse. Such uses of neurotechnology to *explicitly* (knowingly, voluntarily) communicate something or control an application are here included in the category of communication and control. This has been one of the main focuses of BCI research in the past (Wolpaw et al., 2002), although, as we can also see in this study, research focusing specifically on *passive* BCI is gaining in prevalence (Eddy et al., 2019). We also include neurofeedback in this category, in the sense that engaging in neurofeedback is an explicit act to manipulate one's own brain activity or mental state. 9.9% were attributed to this category from among the 110 papers, 11.6% among the $P >= 2$ papers, and 14.3% of the latter minus the methodological papers.

Robots and robotic arms are a popular object of control in the selected literature. For example, Si-Mohammed et al. (2020) used a 6-channel g.tec *g.USBamp* to investigate the use of wireless EEG and steady-state visually evoked potentials (SSVEP) in augmented reality in order to control a robot. Given the robustness of SSVEP signals, this has been a popular method to implement selection using neurotechnology, with several other studies exploring the same (Shao et al., 2020; Chen et al., 2018). Virtual reality, games, and neurofeedback also constitute topics of interest in the communication and control field. For example, an intervention program on 68 patients suffering from mild cognitive impairment using a Cognionics *Quick-20* wireless EEG system based on virtual reality training, reported a significant improvement in cognitive and physical function in the intervention cohort (Thapa et al., 2020). Note that these applications are largely in seated contexts, but Debener et al. (2012b) explored a popular EEG-based control paradigm that is often used for these applications in seated and outdoor walking conditions, using a modified Emotiv device.

Communication and control remains one of the main envisioned use cases for BCI research and development, albeit primarily in clinical conditions, e.g. for patients who have lost other means of communication with the outside world. For healthy participants, communication and control is popular primarily for video games and neurofeedback. These applications do not seem to require wireless EEG as such, but as virtual reality becomes a more popular modality, wireless EEG becomes necessary to allow for the freedom of movement that is an integral part of the experience.

## 5. Discussion and outlook

We have surveyed a number of currently available wireless EEG devices and published works. The search for devices was limited to those obtained from the restricted literature search and an additional Internet search. As such, it is unlikely to provide a complete picture of all devices currently available. This is illustrative of the large number of devices currently on the market, and thus the popularity of the field. In Table 1 and Fig. 2, we see a wide range of devices offering a large variety of configurations for many different use cases, with new electrode designs and novel form factors overcoming issues identified in previous generations. Alongside these hardware improvements, we also see an increasing number of studies making use of the available hardware in a number of different fields.

To provide a comparison between devices, we listed in Table 1 objective criteria primarily related to the tangible properties of the device. We would have liked, of course, to list what is perhaps the main criteria that the reader may be interested in aside from the offered freedom of movement: the signal quality. While some relevant aspects can be inferred to some extent from the objective criteria listed in Table 1, signal quality is ultimately highly dependent on the specific circumstances of any given study: a purely frequency-based analysis of EEG, for example, may not pose the same requirements as one that targets early evoked potentials, and different assessments of 'quality' would apply. Nonetheless, it may be beneficial for the field to develop standardized testing protocols to evaluate wireless EEG devices in order to allow clear side-by-side comparisons. The ERP CORE resource, for example, includes standardized paradigms and analysis pipelines optimized to elicit known event-related potentials (Kappenman et al., 2021). Such resources can be used and extended to mobile settings, e.g. by comparing sitting, standing, and walking conditions using the same device, along with a standardized measure of signal quality, such as the recently proposed standardized measurement error (Luck et al., 2021). Separate protocols could test for a device's range. The absence of such protocols currently leaves technical details such as those listed in Table 1 as the main basis for comparison.

As we mentioned, however, Table 1 is in part based on self-reporting of the manufacturers or licensed distributors, because the requested information was not available from publicly available documentation. Furthermore, the answers provided did not always correspond to the questions asked. While we appreciate the desire to maintain close contact with potential customers, we nonetheless urge all manufacturers to transparently provide the details necessary to make an informed decision without obstruction, and offer the columns of Table 1 as a suggested list of characteristics.

With respect to communication from the manufacturers, we may also briefly return to the issue raised in Section 2, as it remains important to emphasize the mismatch between what may appear to be possible, and what is actually possible. Historically, only researchers and clinicians had access to devices capable of recording EEG. However, recently these technologies have become available to the general public and are sold directly to consumers. Easy-to-use EEG hardware, wireless or otherwise, and accompanying marketing activities foster the imagination, but do little to constrain the consumers' creativity to what is physiologically meaningful. Some vendors make multiple claims that are often not well supported by research literature: Coates McCall et al. (2019) analyzed the most common claims about commercial wearable neurotechnologies, and concluded that scientific evidence supporting utility, safety, and efficacy is rarely provided. As such, important ethical discourses and regulatory frameworks are still lacking, even as the commercialization of neurotechnology continues. We believe it is part of the manufacturers' and distributors' responsibility to inform the public of the possibilities and limitations of their devices, especially to the extent that they engage in direct-to-consumer practices, and provide ready-made metrics of alleged cognitive or emotional states. Studies relying on such metrics should use a design that allows them to be validated before being applied. In this work, we focused our literature search on journal publications with relatively high impact. As such, we attempted to select studies that have undergone more rigorous peer review and achieved peer recognition, and should thus be able to serve as examples to those interested in wireless EEG research.

The difficulty we mentioned in the introduction, with respect to finding a common definition of the various wireless EEG devices, extended to a difficulty in finding appropriate keywords to span the literature. The chosen keywords ultimately reflected the previously chosen definition of wireless EEG. This resulted in a relatively wide variety of results, to which we intended to apply a measure of quality control: The exclusion of conference contributions and focus on journal papers should have resulted in publications subjected to a stronger peer review. The final selection metric, using the mean number of citations per year, is admittedly imperfect, as, e.g., citations do not necessarily reflect quality and it excludes more recent papers from 2021. It was one of the few metrics that could be automatically applied to the >2000 search results, however, and did allow us to focus on apparent high-impact papers.

The sample of 110 selected papers illustrated that while clinical applications, one of the traditional domains of EEG research, remain strongly represented, they have been overtaken in prevalence by a category of cognitive monitoring, in particular for applications that require increased mobility: the use of neurotechnology to detect specific naturally-occuring mental states such as fatigue, engagement, or attention in real-life, unconstrained situations. These are investigated i.a. in automotive, educational, and private contexts, as the advantages of wireless EEG finally allow neurotechnology to leave well-controlled lab environments. Clinical applications focus primarily on seizure detection and sleep stage identification, for which wireless EEG enables unobtrusive, long-term recordings at home. A final category related to communication and control, where SSVEP, motor imagery, and P300 paradigms were the main modalities of control, and were used primarily for gaming or to manipulate robotics.

Our literature review has also revealed a high degree of variability and omissions when reporting methodology and processing pipelines (e.g. study design, data acquisition, preprocessing, statistics), making it difficult to perform metaanalysis and comparison of results across studies. Researchers are encouraged to follow reporting standards such as the OHBM COBIDAS for MEG and EEG guidelines (Pernet et al., 2020), the Agreed Reporting Template for EEG Methodology - International Standard (ARTEM-IS; Styles et al., 2021; Šoškić et al., 2023), and the *good practices for reporting ERPs* (e.g. N400 studies; Šoškić et al., 2022). Following such standards can facilitate a more comprehensive, automated review of the literature in the future. But it is not solely for the sake of reviews that such standards are important. Neuroimaging research in general has been affected by what some call a ‘replication crisis’ (Poldrack et al., 2017; Shrout and Rodgers, 2018), referring to difficulty or even inability to replicate published results. As a response, in the field of EEG initiatives such as *#EEGManyLabs* emerged, aiming to replicate findings of influential EEG experiments (Pavlov et al., 2021). Also worth noting is that in the first years of mobile EEG an encouraging number of results were reproduced, e.g. findings related to auditory oddball in gait (Debener et al., 2012b; De Vos et al., 2014; Scanlon et al., 2019; Ladouce et al., 2019), or gait power modulations (Rogers et al., 2016; Troller-Renfree et al., 2021). Still, it should be remembered that scientific facts, at least in the field of neuroimaging, are rarely established by single papers, but instead rely on the continued work by others who validate and build upon earlier findings. Therefore, to enable EEG research to be of lasting value, it is crucial to adhere to good scientific practices, as e.g. collected in Niso, Krol et al. (2022) for EEG and MEG, and to consider open and reproducible neuroimaging throughout the whole research cycle (Niso, Botvinik-Nezer et al., 2022). These practices include among other things, the preregistration of experiments (Paul et al., 2021; Govaart et al., 2022), the accurate reporting of experiment details using reporting guidelines such as COBIDAS (Pernet et al., 2020) and ARTEM-IS (Styles et al., 2021), and the public sharing of stimulus presentations, data, analysis pipelines and derivatives following e.g. the FAIR guiding principles (Wilkinson et al., 2016) of Findability, Accessibility, Interoperability and Reusability (using public repositories, with persistent identifiers, standardized data and metadata, e.g. following the Brain Imaging Data Structure, BIDS, and appropriate licences). This also includes considerations of sample size, already referenced in Section 4.1.

Thus, keeping in mind some caveats, which any neuroimaging modality has, the currently available wireless EEG hardware provides a broad selection of possibilities, and the literature shows researchers from a diverse set of backgrounds committed to providing the real-world applications that are enabled by these new technologies. Closing the loop, we are seeing short hardware development cycles immediately spurred on by these same research findings—to which we hope the reader is now in a better position to add their own mark.

## Ethics statement

This article did not involve any original data collection on participants and therefore no ethical approval was needed.

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Credit authorship contribution statement

**Guiomar Niso:** Conceptualization, Data curation, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Elena Romero:** Conceptualization, Data curation, Writing – review & editing. **Jeremy T. Moreau:** Conceptualization, Writing – review & editing. **Alvaro Araujo:** Conceptualization, Data curation, Writing – review & editing. **Laurens R. Krol:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing.

## Data availability

No data was used for the research described in the article.

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