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Review article

Home-Based sensing of the nervous system with clinical neurophysiology technologies: IFCN handbook chapter

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ABSTRACT

Background: Home-based neurophysiological monitoring is improving the assessment and management of neurological conditions such as epilepsy. Technologies such as electroencephalography (EEG), electromyography (EMG), and accelerometry are increasingly integrated into wearable systems for at-home use. Due to an increasing amount of data from long-term monitoring, machine learning algorithms assist in automated data analysis. However, ensuring device accuracy, signal quality, and user compliance remains crucial for clinical useability.
Objective: This chapter explores advances and challenges in at-home neurophysiological monitoring, with a primary focus on EEG systems and their applications.
Content: The discussion highlights the technological advances and the challenges associated with at-home monitoring. The focus will be on EEG systems, as well as a discussion of EMG in epilepsy. Next, we will provide an overview of the clinical applications for home-based monitoring of epilepsy and sleep disorders. Lastly, we will briefly discuss emerging topics within home-based monitoring in movement disorders and neurodegenerative disorders.
Conclusion: Future advancements are expected with new generations of wearable systems capable of providing long-term monitoring with minimal maintenance. Beyond epilepsy and sleep disorders, home-based technologies are also being investigated in other neurological diseases including movement disorders and neurodegenerative diseases showing the expanding scope of home-based technologies in neurology.

1. Introduction

Recent advancements in clinical neurophysiology technologies are changing our understanding of and methods for monitoring the nervous system. Traditionally only used at in-hospital and research settings, these technologies can now be implemented for at-home monitoring,

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enabling access to real-time data. In general, home-based sensing offers several advantages as compared to traditional in-hospital monitoring: it is more cost-effective, allows data collection in a naturalistic environment, and enables longer periods of continuous monitoring.

Home-based neurophysiology includes several technologies including EEG, EMG, and accelerometry. These technologies provide insights into neurological diseases such as epilepsy and sleep disorders. Recent improvements in wearable devices and wireless sensors have made it possible to deploy these tools outside traditional clinical settings. The use of machine learning enables the analysis of these large datasets, potentially allowing these technologies to be implemented in clinical practice in the future.

Despite its promise, home-based monitoring comes with several challenges that are still being investigated. Some of the most important issues relate to devices and signal quality, the analysis of large amounts of data, user compliance as well as safety issues. All these issues are important to be able to implement these systems in clinical care.

In this chapter, we will explore the latest technological advances, and the challenges associated with at-home monitoring with a focus on the challenges to applying these methods in clinical practice. The primary methodological focus is on EEG as well as brief discussion of the use of EMG in epilepsy. As several EEG systems exist, we will focus on a few examples that highlight the challenges within the field. To give an overview of the current field of systems and applications for home-based monitoring of epilepsy and sleep disorders, this will be discussed next. Lastly, we will briefly discuss the emerging research on accelerometry in movement disorders and detecting interictal activity in neurodegenerative diseases as examples of new applications.

2. Technology for home-based monitoring

2.1. Home-Based EEG

Electroencephalography (EEG) is an essential tool for diagnosis and management of diseases such as epilepsy and sleep disorders. Traditionally, most EEG recordings in clinical settings have been limited to short-term scalp EEG. However, it is now possible to perform long-term video-EEG monitoring in a home environment. Home-based monitoring offers several advantages, including improved patient comfort, enabling ecologically valid assessments, and reduced costs (Askamp and van Putten, 2014; Nurse et al., 2024).

Prolonged monitoring durations increase the likelihood of capturing infrequent or unpredictable events, such as epileptic seizures, which may not manifest during brief inpatient evaluations (Kandler et al., 2017; Syed et al., 2019). Furthermore, seizures induced in hospital settings, often through medication withdrawal, sleep deprivation or other provocations, may not accurately reflect a patient's typical events and can create a misleading impression of seizure lateralization or localization (Spencer et al., 1981). Monitoring in natural settings ensures the data reflects typical daily activities and sleep patterns, improving the clinical relevance of findings (Hasan and Tatum, 2021). Additionally, home video EEG aids in addressing issues of seizure underreporting and overreporting, both common barriers to accurate diagnosis and treatment (Hannon et al., 2024).

There is an increasing number of devices available, but we will focus on the major categories of systems including wearable and subcutaneous systems. Here, we discuss a subset of EEG systems that are applicable to many use cases. As video monitoring is an important diagnostic tool in combination with EEG recordings, this will be discussed separately from the EEG systems. Besides the EEG systems, it is important to understand the technological challenges including processing large amounts of data, wireless applications, user compliance as well as safety issues.

2.2. Wearable EEG systems

So far, the utility of mobile EEG has largely been limited by usability factors such as comfort, durability, and bulky devices that are obtrusive to daily life activities. Ambulatory EEG monitoring, a cornerstone of mobile EEG systems, records cerebral activity over extended periods in the patient's habitual environment, presenting several unique advantages (Li et al., 2024; Mikhaeil-Demo et al., 2021). However, scalp EEG electrode placement is limited to a few weeks at most, due to the potential for skin injury, inconvenience of visible electrode wires and signal quality degradation with time, requiring technical support.

Other approaches have been developed including the use of dry electrodes to overcome some of these limitations and allow for longer or repeated recordings (Abiri et al., 2019; Di Flumeri et al., 2019; Nurse et al., 2022). Among the various proposed wearable EEG devices using dry electrodes, one approach involves capturing EEG signals from electrodes placed around or inside the ear. While the following discussion is focused on ear-EEG devices, many of the considerations also apply more generally to other wearable EEG technologies.

Ear-EEG refers to EEG recordings obtained with all electrodes, including ground and reference electrodes, positioned around or within the ears, Fig. 1. This approach inherently restricts the spatial coverage of the head and, consequently, the cortical areas being monitored. Thus, ear-EEG is most sensitive to brain sources located close to the ears (Kappel et al., 2019a), limiting the types of phenomena that can be measured using ear-EEG to phenomena that are either generalized and distributed across large areas of the cerebral cortex or originate from sources located close to the ears. This includes sleep analysis (Mikkelsen et al., 2019; Tabar et al., 2023) as generalized phenomena whereas phenomena originating from sources close to the ear includes auditory evoked potentials (BechChristensen et al., 2022; Christensen et al., 2018) and temporal lobe epilepsy (Zibrandtsen et al., 2017).

One of the key advantages of devices like ear-EEG is that it facilitates long-term measurements while being easy to don and doff by the user without requiring assistance. This is, among other things, enabled using dry electrodes. Dry electrodes exhibit significantly higher impedance compared to gelled electrodes, with dry ear electrodes having impedance levels 2–3 orders of magnitude greater than those of conventionally prepared EEG electrodes (Kappel et al., 2019b). The increased electrode impedances introduce several disadvantages including increased noise and potential poorer signal quality. However, some of these can to a certain extent be mitigated using better amplifiers, while others are inherent.

2.3. Subcutaneous EEG systems

Subcutaneous EEG systems offer a middle ground between non-invasive scalp EEG and invasive intracranial EEG. In a controlled environment, subcutaneous EEG signal quality has been shown to be objectively (Weisdorf et al., 2018) and subjectively (Duun-Henriksen et al., 2015) at least as good as overlapped scalp EEG, while several types of artefacts are likely attenuated compared to scalp (sweat, high impedance, movement artefacts) (Duun-Henriksen et al., 2015). These minimally invasive systems provide high signal quality with reduced artifact interference and can be used for ultra long-term monitoring, see Fig. 2. Implanted beneath the scalp, these systems continuously record EEG data over extended periods, providing uninterrupted and high-quality monitoring (Viana et al., 2021). Subcutaneous devices enable the detection of infrequent or nocturnal seizures that might be missed with intermittent monitoring. Their proximity to cortical structures allows for higher-quality signal capture compared to surface electrodes, enhancing the accuracy of data interpretation (Mikhaeil-Demo et al., 2021).

Extended monitoring durations, potentially lasting months or even years, allow for the identification of seizure cycles and rhythms, enabling more accurate diagnoses, tailored medication regimens, and improved seizure prediction (Baud et al., 2018; Stirling et al., 2021). Subcutaneous systems also show promise for future integration with closed-loop systems, facilitating real-time seizure detection and

Fig. 1. Example of ear-EEG. Left to Right: Individualized earpiece with dry-contact electrodes. Ear-EEG ear-piece in the ear. Ear-EEG used for sleep monitoring. Ear-EEG used in real-life monitoring. Photo: Center for Ear-EEG, Aarhus University. Image used with permission from Center for Ear-EEG, Aarhus University. The person depicted provided informed consent.

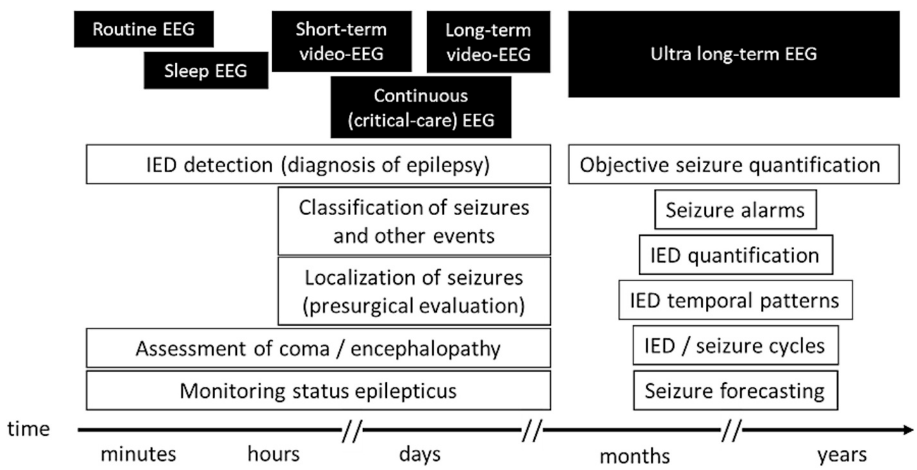

Fig. 2. Different clinical applications (non-exhaustive list) of different EEG recording modalities in epilepsy. Subcutaneous EEG can among other types of EEG devices be categorized as ultra long-term EEG.

intervention to further enhance epilepsy management and patient quality of life (Hasan and Tatum, 2021).

Despite their benefits, subcutaneous devices involve surgical procedures that carry risks, including infection, surgical site pain, lead migration, and skin erosion (Djurhuus et al., 2023). Long-term functionality depends on durable materials and reliable power sources, underscoring the need for continued development in this area (Haneef et al., 2022). In addition, subcutaneous EEG shares the same limitation as wearable EEGs with limited spatial coverage.

2.4. *Intracranial EEG systems*

Another approach is the use of intracranial EEG systems, which have been developed to work as seizure warning systems (Cook et al., 2013) or as closed-loop stimulation devices (Kremen et al., 2018; Skarpaas et al., 2019). Their high signal quality with low contribution of artefacts as well as the possibility of ultra long-term recordings is a clear advantage. However, due to the invasive procedure and possible risk of complications, it is currently limited for broader use. In general, intracranial depth electrodes have a small field of view, while intracranial strips and the subcutaneous devices have a much larger field of view. When short-term (minutes) to long-term (hours to days) recordings have been limited mostly to diagnostic and classification purposes, ultra long-term monitoring offers a range of management possibilities, as highlighted in the section above and conceptualized in Fig. 2.

2.5. *Video monitoring*

Video monitoring can be implemented with any wearable EEG system. Video monitoring enhances home-based EEG by providing visual context, helping clinicians distinguish epileptic from non-epileptic events and improving diagnostic accuracy and can also be used for other behavioral analysis. Specifically, it aids in detecting atypical seizures, clarifying ambiguous EEG changes, and reducing misinterpretation due to artifacts (Benbadis, 2015; Li et al., 2023). Additionally, it engages patients and caregivers by offering insights into seizure patterns, supporting personalized treatment plans, and improving overall patient outcomes (Rocamora et al., 2024; Turco et al., 2021). As described in a recent review, video-monitoring is cost-effective and well received by patients, though challenges remain regarding long-term correct camera placement when the patient is unsupervised at home, and regulatory concerns about data privacy (Brunnhuber et al., 2020).

2.6. *Signal acquisition and processing*

The success of long-term EEG monitoring hinges on reliable signal acquisition amidst daily activities (Zhang et al., 2024), which necessitates power-efficient hardware to sustain continuous operation.

As for the processing of the collected data, continuous recordings can span many days, or even longer with implanted systems, producing in the order of megabytes of data per hour and terabytes of data per year. This requires efficient storage, transmission, and analysis. Manual review of this data by clinicians is labor-intensive and time-consuming, which can be a major obstacle in implementing these systems as clinical tools.

Machine learning has emerged as a promising approach to overcoming these challenges. One application is artifact removal, including motion artifacts and electrical noise (Chen et al., 2022). Additionally, machine learning algorithms can be trained to detect seizure events, differentiate between epileptic and non-epileptic activity, and filter artifacts from both EEG and video data, significantly reducing the burden on clinicians (Gabeff et al., 2021). Furthermore, machine learning can analyze data patterns to identify trends and predict seizure likelihood, enabling personalized management strategies (An et al., 2020). Advanced systems are also being developed to integrate multimodal data, correlating EEG changes with behavioral cues from video recordings to improve diagnostic accuracy (Sahoo et al., 2014). These innovations have the potential to enhance the efficiency and clinical utility of home-based EEG monitoring. However, there is a need for thorough validation of the machine learning methods before they can be implemented in a clinical setting.

2.7. Wireless integration

Wireless connectivity has enabled continuous data streaming to cloud-based platforms (Duun-Henriksen et al., 2020). These platforms offer remote data access for clinicians, who can monitor patients in real-time or review data retrospectively. Secure cloud storage ensures scalability, allowing the accumulation of longitudinal datasets critical for personalized treatment. Hybrid approaches, combining edge computing with cloud storage, are gaining traction. Hybrid devices can process data locally, identifying abnormal patterns such as seizures and either initiating a local intervention or sending an immediate notification to a caregiver or clinician. Simultaneously, these devices can store and upload data for later analysis and statistical evaluation. However, several issues still exist including data security as well as handling data transmission and real-time processing of the EEG data.

2.8. User compliance and safety

Patient training and support are essential to optimize home-based monitoring. Previously, it has been suggested that instructional programs and ongoing technical assistance is needed for patients to use the equipment confidently (Musaeus et al., 2022), which also improves compliance and data reliability (Stefan et al., 2011). However, modern systems are being developed that makes it more intuitively to use the devices without support. As previously shown patients are in general eager to use the systems in the beginning, but use is reduced over longer periods (Olsen et al., 2021).

Additionally, handling sensitive neurological data requires stringent security measures as any breach of data can be an issue for patient safety and confidentiality. To this, modern home EEG systems routinely employ secure data transmission and storage protocols (Lado and Kuzniecky, 2024). In addition, there may be legal issues in data storage and transmission that could make implementation of these systems challenging.

2.9. Barriers to adoption and future considerations

While home-based EEG monitoring offers numerous benefits, it also presents challenges, particularly in ensuring high-quality data collection outside hospital settings. Reliable data acquisition in a home environment requires robust and user-friendly equipment (Lawley et al., 2015). Although multiple types of systems exist, there is still a need for observational studies to fully understand the signal quality and patient compliance. Another issue is prolonged wear as this can lead to discomfort and dropout. Furthermore, the reliance on wireless technology necessitates robust cybersecurity measures to protect patient data as well as to prevent corrupted data, which can cause safety issues in treatment.

2.10. The future of home-based EEG

As machine learning analysis, and improved EEG systems emerge, home-based EEG can become a very usefultool for diagnosis and treatment. Continued innovation in wearable technologies, signal processing, and development of systems that are easy to use are still needed for robust and accessible solutions. The recent advancements in technology and patient compliance have increased the feasibility and reliability of home-based EEG and video-EEG monitoring and it is possible that they may become alternatives to some types of in-hospital observation as well as provide recordings that are not possible to collect with the conventional methods.

2.11. Seizure detection and characterization using surface electromyography

Another approach for seizure detection is electromyography (EMG). Muscles are connected via synapses (neuromuscular junctions) to the motor nervous system. Therefore, electric signals from muscles, recorded during seizures, using surface electrodes (EMG) provide direct evidence for ictal pathophysiology (Beniczky et al., 2016).

Qualitative interpretation of EMG signals recorded in epilepsy monitoring units provides valuable clinical information regarding motor seizures (Marcinski Nascimento et al., 2024). Quantitative analysis of EMG during seizures showed that tonic seizures and tonic-clonic seizures are associated with increased activity in the high frequency EMG activity. Furthermore, increased intra-muscular synchronization leads to increased EMG amplitude during the tonic phase of tonic-clonic seizures (Beniczky et al., 2016; Conradsen et al., 2011b).

Moreover, the dynamic evolution of the clonic phase, consisting of progressively increasing silent periods between clonic jerks (Conradsen et al., 2013) accurately differentiates between psychogenic and epileptic convulsive seizures (Beniczky et al., 2014).

Based on the quantitative EMG changes specific for seizures, neurophysiological seizure-biomarkers have been identified and validated (Beniczky et al., 2016; Conradsen et al., 2012a, 2012b; Conradsen et al., 2012b). This relies on the specific increase in power in the high frequency domains, simultaneous with increase in amplitude of the EMG signal. The algorithm developed using this biomarker was tested in a phase-3, prospective, multi-center clinical validation study, using a predefined ("fixed-and-frozen") algorithm and detection-threshold, implemented on a wearable surface EMG device, for real-time detection of tonic-clonic seizures (Beniczky et al., 2018a). The sensitivity of the wearable EMG device was 94 % (30 out of 32 GTCS were detected). Median seizure detection latency was 9 s. False alarm rate was 0.67/24 h – mainly during the active daytime periods (0.01 false alarms / night).

Detection of tonic seizures with surface EMG remains a challenge. Using personalized algorithms, a study with prospective data-collection and retrospective analysis, achieved sensitivity up to 100 %, yet at the cost of false alarms between 0.08 and 7.9 per hour (Larsen et al., 2014).

EMG signals provide valuable information beyond seizure detection. Using the algorithm targeting the neurophysiological biomarker, automated differentiation between psychogenic and epileptic convulsive seizures using surface EMG achieved an accuracy of 95 % (Beniczky et al., 2015). Using machine learning and the correlation between seizure-dynamics and the postictal generalized EEG suppression, an algorithm was able to identify the seizures with high risk for sudden unexpected death in epilepsy (SUDEP) with an accuracy of 85 % (Arbune et al., 2020).

In conclusion, there is compelling evidence that wearable EMG devices can accurately detect tonic-clonic seizures (Beniczky et al., 2018b). This approach may also be useful for automated differentiation between psychogenic and epileptic convulsive seizures (Beniczky et al., 2015) and estimate seizure severity / the risk of SUDEP (Arbune et al., 2020).

3. Clinical applications

3.1. Home-based epilepsy monitoring

Currently, the clinician is heavily dependent on information from relatives and patients when identifying seizures. However, studies have suggested that the patient's history is unreliable even when reported from relatives (Blachut et al., 2015; Cook et al., 2013; Elger and Hoppe, 2018; Hoppe et al., 2007; Tatum et al., 2001). There is a need for long-term EEG recordings to both diagnose and guide clinicians in selecting the right type of treatment. Such as with other chronic, particularly dynamic health conditions, mobile health solutions offer a diverse range of opportunities to improve clinical care in epilepsy. In the previous chapters we have discussed EEG and EMG, but other types of mobile devices are currently being developed, and mobile devices have several clinical applications in epilepsy (Table 1).

Seizure detection devices have typically used single modalities or combinations of EEG (Baumgartner and Koren, 2018), video (Pediaditis et al., 2012), accelerometry (Nijsen et al., 2005), electromyography (Conradsen et al., 2011a), electrocardiogram (Zijlmans et al., 2002), photoplethysmography (PPG) and electrodermal activity (EDA) (Poh et al., 2010).

Seizure detection can be performed both in real-time and retrospectively, serving different purposes. Seizure detection in "real-time" may serve an important role to protect people with epilepsy against seizure-related harms. For example, it could be employed as a seizure alarm to summon help, to activate a protective device (Gutierrez et al., 2018), or activate therapy as in a closed-loop stimulation device (Fisher et al., 2016). Furthermore, it may include treatment modulation according to risk including fast-acting medication/chronotherapy and neuromodulation to patient behavior modification and protection, ultimately improving safety and quality of life (Baud and Rao, 2018; Grzeskowiak and Dumanis, 2021).

As for retrospective detection, due to the unreliability of self-reported seizure diaries (Elger and Hoppe, 2018), an accurate seizure detection device, could be used to optimize medical treatment, avoiding undertreatment due to unreported seizures, and minimizing unnecessary side-effects due to seizure over-reporting. An accurate seizure detection device could also provide objective seizure statistics in clinical trials of new antiepileptic drugs and other epilepsy treatments, which currently depend entirely on patient self-reported seizure diaries. In addition, retrospective review may contribute to the diagnosis of non-epileptic paroxysmal events, from psychogenic seizures (Bayly et al., 2013; Beniczky et al., 2015; Kusmakar et al., 2016) to cardiogenic events. Seizure detection devices may also be studied for their potential to measure disease severity, for example, associated with SUDEP risk (Beniczky et al., 2020), ictal autonomic changes (Poh et al., 2012), ictal surface electromyography patterns (Arbune et al., 2020), post-ictal immobility (Bruno et al., 2020a), and post-ictal central apnea (Vilella et al., 2019) are all potentially measurable by mobile devices and are associated with post-ictal generalized electroencephalography (EEG) suppression, a risk factor for SUDEP.

For a device coupled with closed-loop stimulation, a higher false alarm (and consequently, stimulation) rate will be much more tolerable and might not even be noticed by the patient (Brinkmann et al., 2021). For example, in the pivotal trial for a responsive neurostimulation device (Heck et al., 2014), the goal was to detect epileptiform activity and then stimulate cortex to abort seizures. The system parameters detected and stimulated a median of ~ 2800 episodes per day, or approximately 84,000 stimuli per month, in a subject population who reported a median of 8.7 seizures per month. Thus the detection rate, and hence, the stimulation rate, vastly exceeded seizure frequency by a factor of10,000. Yet, we do not fully understand if this has any long term consequences, like kindling of changed inflammatory state. In the short range it seems that the benign, asymptomatic nature of the intervention made this detection algorithm tolerable and was proven beneficial.

Another crucial point is whether the detection method is robust and generalizable. Recently published standards of testing and validation of seizure detection devices have been proposed, where performance is tested and validated only in the epilepsy monitoring unit (EMU) with concurrent video-EEG (Beniczky and Ryvlin, 2018). This is a highly controlled environment where even simple daily activities such as walking or running do not normally occur. Final phase, in-field (at-home) studies do not use performance as a study outcome, as there is no accepted "gold-standard" outside the EMU to test it against. One approach is to compare to home EMU monitoring, but this only solves part of the issues when comparing gold standard to home-based EEG.

An additional essential requirement is device acceptability. Several studies have shown that people with epilepsy are willing to use wearable devices for continuous health monitoring (Bruno et al., 2018; Hoppe et al., 2015; Tovar Quiroga et al., 2016). However, attention should be given to device design to address the requirements and preferences of people with epilepsy and caregivers. Key factors affecting a device's usability relate to its design (attractive appearance, low visibility, low intrusiveness), comfort of use, confidentiality of recorded data, and timely support from both technical and clinical ends (Bruno et al., 2020b).

Table 1
Example clinical applications of mobile devices in epilepsy.

Method / Use Case	Example applications
Real-time seizure detection	• Real-time alarm for patient or caregiver (e.g. for rescue medication, protection) • Potential prevention of SUDEP • Earlier intervention for status epilepticus or seizure clusters • Closed-loop stimulation (e.g. vagus nerve stimulation, deep brain stimulation, responsive neurostimulation)
Offline seizure detection	• Accurate seizure counting (mitigate side-effects from excessive medication; avoid undertreatment) • Disease burden quantification (seizure severity assessment) • Safety for driving or other potentially risky activities • Clinical trials • Differential diagnosis of paroxysmal episodes (PNES, cardiac) • Personalized information for patients (improving patient self-knowledge, confidence)
Seizure forecasting / prediction	• Planning of daily life activities • Preventative measures before seizure (e.g. protection, fast-acting medication) • Plan investigations (e.g. video-EEG) • Mitigate uncertainty • Better recognition of seizure triggers / precipitants
General health monitoring	• Sleep monitoring • Activity tracking • Monitoring and screening for comorbidities (e.g. cardiovascular disease)

3.2. Overview of available mobile devices in epilepsy

There are currently several types of mobile devices available aimed at seizure detection (Bruno et al., 2020b). See Table 2.

Most devices use unimodal or multimodal non-EEG based sensors. Most are approved to detect tonic-clonic seizures or seizures with prominent motor components only (Bruno et al., 2020b).

Under-the-bed-mattress sheets (EmFit, Medpage), restricted to detect seizures in bed, may be useful in people with nocturnal epilepsy or those in residential homes. So far, variable sensitivity (as low as 11 %) and false alarm rates as high as 4/night have been reported (Carlson et al., 2009; Fulton et al., 2013; Narechania et al., 2013; Poppel et al., 2013). Surface EMG detection bands (Brain Sentinel SPEAC, SeizureLink), strapped to a patient's biceps, have been approved to detect tonic-clonic seizures (Beniczky et al., 2018a; Halford et al., 2017). Reported sensitivity is high, but the device needs to be correctly attached (Halford

Table 2
Available mobile devices for seizure detection.

Device type	Tonic-clonic Seizures	Other motor seizures	Nocturnal seizures	Non-motor seizures with ictal autonomic changes	Non-motor seizures without ictal autonomic changes
Under mattress sheets (Arends et al., 2018; Carlson et al., 2009; Fulton et al., 2013; Narechania et al., 2013; Poppel et al., 2013)	+	+/-	+	–	–
Unimodal wristwatches (Beniczky et al., 2013; Lockman et al., 2011; Meritam et al., 2018; Patterson et al., 2015; Velez et al., 2016)	+	+/-	+/-	+/-	–
Multimodal wristwatches (Caborni et al., 2017; "https://www.accessdata.fda.gov/cdrh_docs/pdf18/k181861.pdf," n.d.; Poh et al., 2010; Onorati et al., 2018, 2017; Regalia et al., 2019)	+	+/-	+/-	+/-	–
sEMG armbands (Beniczky et al., 2018a; Cardenas et al., 2020; Halford et al., 2017)	+	+/-	+/-	–	–
Multimodal armbands (Arends et al., 2018)	+	+/-	+/-	+/-	–
Camera systems (Peltola et al., 2023)	+	+	+	–	–
Wearable ECG patch (Jeppesen et al., 2024)	+/-	+/-	+/-	+	–

+ published performance/device approval; +/- limited evidence/not approved; – no evidence/not approved.

et al., 2017); false alarm rates derived from studies in the EMU setting range from 0.014 to 2.52 per day, although this is expected to significantly increase in ambulatory settings. Approved wrist-worn devices (Empatica Embrace, Nightwatch, Epi-Care) use single or combination of sensors aimed at detecting movement (accelerometry, gyroscope) and ictal / *peri*-ictal autonomic activity (electrodermal activity, photoplethysmography, temperature). Still, their approval is restricted to major motor seizures. For these seizure types, reported sensitivities (mostly assessed offline) are usually above 90 %, while false alarm rates run below 1 per day (Arends et al., 2018; Beniczky et al., 2013; Onorati et al., 2017; Regalia et al., 2019).

A limited number of in-field phase (i.e. ambulatory) studies have been conducted using these devices (Meritam et al., 2018; Picard et al., 2017; Thompson et al., 2019). These studies assessed aspects related to quality of life and satisfaction of usage of the devices. Reported sensitivities and false alarm rates were limited to the fact that they were compared to patient/caregiver seizure diaries.

The opinion of patients and caregivers on specific devices was assessed in some studies. The possibility to increase safety and improve the independence of both patients and caregivers was praised for some devices (SmartWatch Inspyre (Thompson et al., 2019), Nightwatch (Arends et al., 2018)) despite concerns about false alarms and additional burden to epilepsy care (SmartWatch Inspyre (Thompson et al., 2019)). Similar studies reported devices design and form to be overall acceptable and comfortable (Nightwatch (Arends et al., 2018), Epi-Care Free / Mobile (Meritam et al., 2018)) except for specific contexts (e.g. Brain Sentinel SPEAC during sleep (Halford et al., 2017)).

3.3. Sleep monitoring

The reference standard of sleep measurement is the polysomnography (PSG) (Rundo and Downey, 2019), but requires specialized equipment, is expensive, and can be uncomfortable for the participant. In general, PSG combines biometrics of limited channels of EEG, eye movement, submental electromyography, sound, and monitoring of several cardio-respiratory domains. Recently, several types of sleep wearables have been developed (de Gans et al., 2024) with the most promising classifying sleep stages being the EEG-based systems (Imtiaz, 2021), which has been implemented for home-based monitoring.

So far, a whole range of different types of systems for home-based sleep monitoring exist as demonstrated in a recent review that identified 24 distinct EEG based wearables for sleep monitoring (de Gans et al., 2024). The types of equipment ranged from headbands (Tonetti et al., 2013), ear-EEG (Mikkelsen et al., 2019; Tabar et al., 2023) to single channel EEG as well as forehead multiple sensor patches. Of all the available devices, the review found that ten EEG-based devices demonstrated general effectiveness and user tolerance (de Gans et al., 2024). Although the studies have found promising results, there is still a need for validation in a larger cohort of patients.

In addition to EEG-based devices, other home-based sleep monitoring systems utilize non-EEG approaches such as actigraphy and photoplethysmography (PPG) (Mohamed et al., 2023). Actigraphy devices, commonly integrated into wristbands or smartwatches, estimate sleep patterns by analyzing movement data. Thus, subjects lying still in bed before falling asleep may be reported as already sleeping. Actigraphy also lacks the precision of EEG for detailed sleep stage classification since there is no clear correlation between movement and sleep stage (Ancoli-Israel et al., 2003). PPG-based systems, often embedded in smartwatches or rings, monitor changes in blood volume using light sensors, enabling the estimation of heart rate variability and potential insights into sleep stages (Ryals et al., 2023). Although these alternatives provide convenience and accessibility, they often trade accuracy for ease of use compared to PSG and lack the precision of EEG-based systems.

Despite their potential, the performance of at-home sleep monitoring systems is highly device-dependent and influenced by factors such as signal quality, user compliance, and specific algorithms used for analysis. If the focus is solely on sleep macro-structure—such as sleep stages and derived sleep metrics—many EEG-based devices have demonstrated performance comparable to conventional PSG. However, when the outcome measures involve sleep micro-events, REM sleep without atonia detection, or the identification of central apnea, the accuracy and reliability of these devices is worse. In addition, some of the methods for sleep analysis has been purely trained on healthy younger subjects and more work is needed to validate these findings in patient populations. Future directions for research include enhancing device accuracy, reducing user burden, and exploring multimodal approaches that combine multiple biometric signals to provide a more comprehensive assessment of sleep.

3.4. Home-based accelerometry in movement disorders

Self-reported scales, such as the Unified Parkinson's Disease Rating Scale (UPDRS) – Part II (motor experiences of daily living) (Goetz et al., 2008) and the Multiple Sclerosis Impact Scale (MSIS-29) (Hobart, 2001), are widely used in neurological populations to assess patients' perceptions of their movement, physical activity, and mobility. However, these self-reported measures have notable limitations, including subjectivity, recall bias, and limited granularity (Jørstad-Stein et al., 2005; Shiffman et al., 2008). Clinician-administered assessments, such as the Abnormal Involuntary Movement Scale (AIMS) (Guy, 1976) and UPDRS Part IV (motor complications) (Goetz et al., 2008), provide more objective and standardized evaluations through direct clinical observation. Nevertheless, these clinician-administered scales also have notable limitations, such as infrequent assessments, dependence on clinical visits, and the inability to capture fluctuations or subtle changes occurring during daily life.

Wearable inertial measurement units (IMUs) offer a non-invasive, continuous, and objective method for tracking movement and physical activity during daily activities at home as well as movement during sleep. IMUs capture 3D acceleration and angular velocity, with the option to include a magnetometer for improved orientation tracking. Previous reviews have demonstrated the effectiveness and widespread adoption of IMU-based activity monitoring in neurological populations (Block et al., 2016; Giggins et al., 2017). Particularly, IMUs can reliably track various activity and movement metrics such as step count, distance travelled, physical activity intensity, walking speed, and energy expenditure (Giggins et al., 2017). However, this type of monitoring primarily focuses on movement quantity rather than movement quality, potentially lacking the necessary detail to accurately assess disease severity and progression.

In addition to basic activity and movement metrics, IMUs used to monitor daily activities at home generate large volumes of raw motion data, which are difficult for humans to interpret directly. To translate these data into meaningful insights related to motor symptoms and disease progression, such as gait abnormalities, weakness, and spasticity, machine learning models are increasingly being applied (Alberdi et al., 2018; Boukhennoufa et al., 2022; Yang et al., 2024). Machine learning focuses on developing algorithms that can identify patterns and learn from observed data (Jordan and Mitchell, 2015; LeCun et al., 2015). A variety of machine learning methods are available, including regression techniques, which predict continuous outcomes (e.g., scores on standardized assessments), and classification models, which assign categorical labels (e.g., identifying the presence of tremor). For example, a recent study applied a machine learning-based freezing of gait detection algorithm to continuous 24/7 IMU data, yielding valuable insights into how medication timing and time of day may affect symptom severity (Salomon et al., 2024). Hence, IMU data combined with machine learning has great potential in improving long-term care for individuals with neurological conditions.

Despite these advancements, the integration of machine learning with long-term IMU data into clinical practice remains limited. One major challenge is that IMU data alone do not fully capture intrinsic (e.g., stress levels, anxiety, cognitive function, medication status, fatigue) and extrinsic factors (e.g., static and dynamic environmental elements providing somatosensory, visual, or auditory stimuli), all which influence symptom manifestation in home environments (Mancini et al., 2025). To accurately interpret home activity and mobility data and extract clinically relevant insights, it is essential to capture both sets of factors (Gaßner et al., 2020). A promising development is the use of machine learning methods that combine IMU data with other physiological sensors, enabling the capture and quantification of both sets of factors and their effect on motor symptom expression (Cockx et al., 2023; Katmah et al., 2023; Yang et al., 2025). This integrated approach shows great potential for advancing personalized monitoring and intervention strategies in the management of neurological conditions. However, further validation through longitudinal clinical studies is needed to fully establish effectiveness, reliability, and clinical utility.

3.5. Spike detection in neurodegenerative diseases

One emerging topic is the possible association between neurodegenerative diseases and epileptiform discharges. In patients with Alzheimer's disease (AD), studies have found that 22 %-75 % showed epileptiform discharges without clinical seizures (Horvath et al., 2021; Lam et al., 2020; Musaeus et al., 2023a; Vossel et al., 2016). So far, this has also been investigated in a small study involving patients with Lewy body dementia with similar findings (Musaeus et al., 2023b). The interest in this area is mainly due to the findings of an association with a more rapid rate of progression in patients with epileptiform discharges (Horvath et al., 2021; Vossel et al., 2016) and a potential effect of anti-seizure medication in patients with AD (Musaeus et al., 2017; Press et al., 2023; Vossel et al., 2021).

An important aspect of detection is the length of the recordings. Using conventional scalp EEG, 3 % of patients in a memory clinic cohort had at least one epileptiform discharge (Liedorp et al., 2010), whereas this number is up to 54 % using 24-hours long-term EEG recordings (Horvath et al., 2021). In a more recent study using up to two days of out-patient ear-EEG recordings, 75 % of the patients had at least one epileptiform discharge with considerable variation between ear-EEG recordings (Musaeus et al., 2023a). However, in the healthy controls, the number participants with epileptiform discharges also increases. Although in-patient long-term EEG recording is the "gold standard", an inexpensive out-patient monitoring may improve our understanding the role of epileptiform discharges in neurodegenerative diseases.

The field of long-term out-patient monitoring for epileptiform discharges is not well investigated and so far, ear-EEG has been the only type of out-patient monitoring used. Here, there are several issues with being able to separate epileptiform discharges from artifacts using mobile EEG systems with low spatial resolution. When using ear-EEG simultaneously with long-term surface EEG monitoring, a study found that it was possible to detect similar epileptiform discharges with ear-EEG (Zibrandtsen et al., 2017). There has, however, never been performed any investigation of the sensitivity or specificity of long-term out-patient EEG monitoring for epileptiform discharges using at-home monitoring.

4. Future of home-based monitoring

The future of home-based monitoring and implementation into clinical practice is likely to be shaped by advancements in both device technology and machine learning-driven data analysis. Wearable and subcutaneous EEG systems, along with EMG monitoring, have expanded the options for home-based neurophysiological assessment. In addition, there is a potential in multimodal sensing, which still needs to be explored. These technologies hold potential to be implemented in clinical practice possibly as a supplement to current monitoring methods. However, there is still a need for improvement in both signal quality as well as improved comfortability for the patients for wearable and subcutaneous EEG.

In general, multiple relevant scenarios for long-term monitoring exist, each with distinct implications. In some cases, recording may be needed over a few days or weeks, for example, when screening for epilepsy or sleep disorders. In other situations, recording over weeks or months, or at repeated intervals over several years, may be useful. For instance, monitor disease progression or assess the effects of an intervention. In other cases, continuous, perpetual recording may be required, such as for epilepsy monitoring and warning devices. Each of these scenarios presents different requirements in terms of usability, discretion, durability, and other practical considerations and the subsequent use of long-term EEG monitoring devices.

An important issue with implementation of these technologies is the large amount of data that is generated, which requires development of machine learning methods for automatization or at least semi-automatization of the data analysis. Before machine learning methods can be implemented in clinical care, there is a need for validation of the methods to understand their limitations and imperative biases across different patient populations and clinical settings. For most patients and caregivers, real-time feedback and alert mechanisms are of extreme importance, whereas clinicians require proactive tools to manage conditions dynamically. Due to the advancements of home-based monitoring and the corresponding machine learning methods, the technology is likely to be applied more broadly, encompassing other neurological diseases. This can for example be the detection of epileptiform discharges in patients with neurodegenerative diseases, with potential implications for understanding disease progression. Additionally, motion analysis is furthering our insights into motor impairments, enabling both detection of early signs of a disease as well as the monitoring of the efficacy of interventions for individuals Parkinson's disease, multiple sclerosis, and stroke.

Since long-term home-based monitoring is more cost-effective, allows data collection in a naturalistic environment, and enables longer periods of continuous monitoring, it is likely that more types of systems will be implemented in the care of neurological patients in the future. However, before these types of technologies can be implemented, there are several technological advances that needs to be addressed including improving the user-friendliness of devices, stable signal acquisition as well as understanding the limitations of the developed machine learning methods. The future of home-based monitoring is likely a dynamic interplay of technology and clinical application, which requires both technical improvements as well as clinical investigations to understand the patients' needs.

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Further reading

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