Commercial Wrist Devices for Epileptic Seizure Detection: A Systematic Review

Andrea Caroppo, Andrea Manni, Anna Maria Carluccio, Gabriele Rescio and Alessandro Leone
National Research Council of Italy - Institute for Microelectronics and Microsystems
Via Monteroni, c/o Campus Università del Salento, Palazzina A3, Lecce, Italy
email: andrea.caroppo@cnr.it, andrea.manni@cnr.it, annamaria.carluccio@imm.cnr.it, gabriele.rescio@cnr.it, alessandro.leone@cnr.it

***Abstract*—Several movement disorders with a wide range of motor and non-motor symptoms have been identified in the medical field. Incorporating wearable sensors in rehabilitation and disease management applications has seen its fair share of growth over the past few decades, with a significant increase in monitoring movement disorders. In this recent period, it is quite evident how ingenious wrist devices, such as wristbands, smart bracelets, and smartwatches are growing increasingly popular among all age groups. The ease of use, inexpensiveness, and higher degree of acceptability in contrast to other categories of sensors employed to monitor health status offer reasons for this diffusion. This recent review of the literature intends to collect studies that exploit commercial smart wrist devices for one of the more well-known movement-related disorder considered to be prevalent among the world's population of all ages: seizure detection or epilepsy. Here, the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) methodology was used to select and analyze 19 articles. For each article, information is given on the type of sensor used, any pipelines implemented, and classification results obtained. Almost all the studies were published within the last decade indicating an increasing interest in the scientific community for the considered topic.**

Keywords- smartwatch; wristband; bracelet; wrist-worn, movement disorders; epilepsy; seizure detection.

I. Introduction

Patients with many kinds of diseases have been admitted to hospitals and private nursing homes in greater numbers in recent years. The aging of the global population is the primary cause of this increase, even though numerous studies document a notable rise in therapeutic and pharmaceutical treatment approaches. This incentive has gradually encouraged technology companies to develop affordable, user-friendly devices that are appropriate also for elderly people. In addition to companies, researchers also utilize wearable technology to explore specific clinical conditions. Among the most investigated of the latter, we find the category of movement disorders, which are widely prevalent in the global population of young people and adults.

Due to the typical integration of sensors like the gyroscope, accelerometer, and magnetometer, commercial smartphones may now conduct a large-scale assessment of movement disorders, of which most people worldwide suffer. Furthermore, a growing number of smartphones have processing units, enabling programmers to develop computational pipelines that execute in real-time directly into the device. As a result, the market for applications that offer information about movement disorders has grown in recent years, often for free. A fascinating and recently published review article lists and discusses the applications created to identify, track, evaluate, or treat movement disorders by smartphones [1]. However, the smartphone is wrongly considered a wearable device. Although for most of the day, it is held in the hand of the end-user, it is often placed within the living environment in different locations (tables, desks, bedside tables), and this is more frequent when considering the use of such devices by frail and elderly individuals. Consequently, it may be inconvenient to use smartphones to assess, for example, changes in movement disorders for which continuous monitoring is required.

Unlike the smartphone, a smart wrist device is like a wearable computer that comes in a variety of forms, dimensions, and features. Depending on the possession of these characteristics, such a device is called a smartwatch, bracelet, or wristband. Large-scale gathering and analyzing of data that would have seemed impossible in the past are now made possible by the widespread use of smart wrist devices. This is a developing trend that has the potential to increase our understanding of various diseases [2][3] significantly. Movement disorders cover a wide variety of neurological illnesses, including hypokinetic and hyperkinetic disorders, as multiple publications have demonstrated. Decreased motions, such as stiffness and akinesia/bradykinesia, are indicative of hypokinetic movement disorders. On the other hand, excessive movements and a variety of motor symptoms are hallmarks of hyperkinetic movement disorders.

One of the most prevalent hyperkinetic movement disorders is epilepsy, which affects approximately 1% of people worldwide [4] and causes 20.6 million disability-adjusted life years lost. The most common feature of epilepsy is an increased brain tendency to have epileptic seizures, which can have severe neurobiological, cognitive, psychological, and social consequences. Up to one-third of people with epilepsy still experience recurrent seizures even after decades of developing new medications and undergoing surgery [5]. Epileptic seizures are sudden, potentially fatal episodes that can threaten the lives of both the individual with epilepsy and others, even though most people spend more than 99.9% of their lives without experiencing any symptoms. Accurate monitoring and tracking of epilepsy or seizures are important to evaluate seizure burden, recurrence risk, and response to treatment. Outside the hospital, seizure tracking relies on patients' and families' self-reporting, which is often unreliable due to underreporting, seizures missed by caregivers, and patients' difficulties recalling seizures [6][7].

While the gold standard for accurately diagnosing and evaluating epilepsy in the Epilepsy Monitoring Unit (EMU) is long-term Video-Electroencephalography (EEG) [8], such technology turns out to be expensive and time-consuming. Previous research indicates that there is a significant clinical gap and an urgent medical need to identify a wide variety of seizures or epilepsy with wearable devices [9][10][11].

Also, the COVID-19 pandemic that hit the population in 2020 created significant disruptions in clinical practice, the main effect of which was the spread of remote medicine to provide clinical care [12]. To address this gap and enable continuous patient monitoring in the outpatient setting, new developments in the use of non-Electroencephalography-based seizure detection systems that employ a range of sensors and modalities have emerged, including smart wrist devices which, among other categories of wearable sensors, are more tolerated by patients over time and less stigmatizing [13].

The main aim of this literature review is to provide a collection of the most recent research advancements made in the field of smart wrist devices for monitoring epilepsy or seizure detection. The primary objective is to provide a recent state of the art that will help medical staff, caregivers, researchers, and engineers involved in the development of solutions in these research areas, along with a general idea of recent trends and future developments.

This paper is organized as follows: after this introductory section, Section II explains the criteria adopted for the selection of the articles in this review, whereas in Section III a brief description of each article included in this review is given. Finally, Section IV draws some conclusions and final remarks.

II. MATERIAL AND METHODS

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) was adopted in this review article as the systematic review methodology [14].

The PRISMA guidelines consist of a four-phase flow diagram and a 27-item checklist. The flow diagram describes the identification, screening, eligibility, and inclusion criteria of the reports that fall under the scope of a review. Two databases were searched, including Scopus and PubMed, to identify relevant studies published from 2014 until July 2024. The search strategy included a combination of keywords and terms related to smartwatches, bracelets, wristbands, and epilepsy or epileptic seizures. The structured queries for extracting items for analysis were selected based on the following question: “How are smartwatches, bracelets, or wristbands used to provide information about epilepsy or epileptic seizure?”.

To use the search functionalities provided by the two scientific databases under consideration, two queries were defined that vary slightly in their syntactic composition but not in their keyword definition. The queries used are shown in Table I.

A. *Article selection, Inclusion, and Exclusion criteria*

The queries in Table 1 returned a total of 186 articles (111 from Scopus, and 75 from PubMed). Only articles produced within the last 10 years, starting from January 2014, were selected. In the screening phase, 71 duplicates were first eliminated, along with 2 other articles that, although returned as results from the search query, have no relevance to the topic investigated. Then, the remaining articles (113) were analyzed by title and abstract, after checking the availability of the full text. The eligibility criteria for inclusion in the review were:

- articles published in an indexed journal (conference abstracts, workshop results, preprint articles, book chapters, and posters were not considered for inclusion in the review).
- articles in which a smart wrist device is used (both commercial and prototype).
- articles presenting results from studies where data were collected using humans.

On the other hand, the eligibility criteria for exclusion in the review were:

- articles in which the device used for the assessment of the movement disorder is not wrist-worn.
- articles that do not provide information on movement disorders.
- articles containing reviews, surveys, or proceedings.
- articles not produced in the English language.
- articles downloadable only against payment.

Next, 37 articles needed to be screened once the inclusion and exclusion criteria were defined, and a more in-depth reading was necessary for these articles. Specifically, the internal content of each paper was examined to incorporate into the review only articles that used the raw data acquired from the wrist device to classify epilepsy or seizure. In the final analysis, 19 articles satisfied the inclusion requirements and were taken into consideration for the proposed literature review. Figure 1 shows the study selection procedure.

TABLE I. SEARCH QUERY AT VARYING OF EACH CONSIDERED MULTIDISCIPLINARY DATABASE

Database	Search query
Scopus	TITLE-ABS ((("Smartwatch" OR "Smartwatches" OR "Wristband" OR "Wristbands" OR "Brace-let" OR "Bracelets" OR "Smart watch" OR "Wrist-worn" OR "Wrist device" OR "Wrist devices" OR "Actigraph" OR "Apple watch" OR "Garmin" OR "Fitbit") AND ("Epilepsy" OR "Seizure")))
PubMed	((Smartwatch[Title/Abstract]) OR (Smartwatches[Title/Abstract]) OR (Wristband[Title/Abstract]) OR (Wristbands[Title/Abstract]) OR (Bracelet[Title/Abstract]) OR (Bracelets[Title/Abstract]) OR (Smart watch[Title/Abstract]) OR (Wrist-worn[Title/Abstract]) OR (Wrist device[Title/Abstract]) OR (Wrist devices[Title/Abstract]) OR (Actigraph[Title/Abstract]) OR (Apple watch[Title/Abstract]) OR (Garmin[Title/Abstract]) OR (Fitbit[Title/Abstract])) AND ((Epilepsy[Title/Abstract]) OR Seizure[Title/Abstract]))

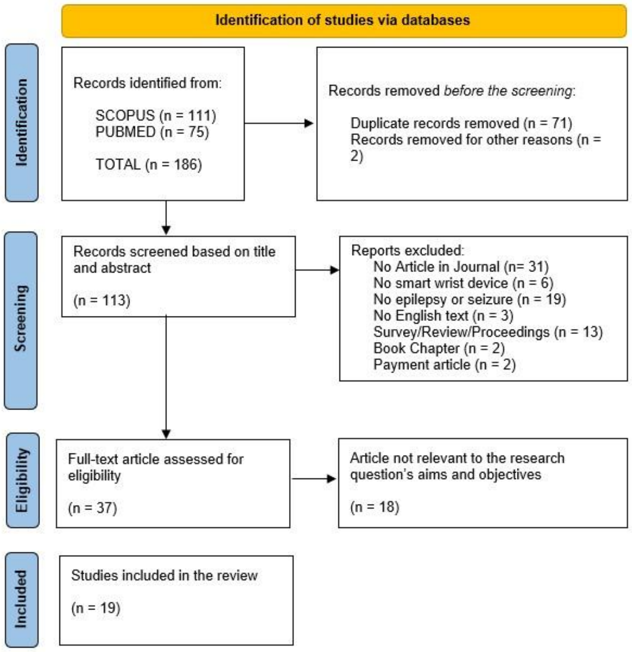

Figure 1. Flow diagram generated with PRISMA methodology, depicting the reviewers' process of finding published data on the considered topic and how they decided whether to include it in the review.

III. RESULTS

Many medical studies indicate that a person with epilepsy has two or more unprovoked seizures that happen more than twenty-four hours apart. Instead, depending on which areas of the brain are affected, an excessive spike in electrical activity in the brain, known as a seizure, can produce a range of symptoms. It follows that the words "seizure disorder" and "epilepsy" are often used interchangeably. However, "provoked" seizures, such as those due to severe hypoglycemia, are not considered to be forms of epilepsy. A consequence of all the above considerations is that the articles included in the present literature review concerning the use of smart devices for epilepsy also discuss using the wrist device, commercial or otherwise, for seizure detection.

The authors of [15] designed and developed an electronic device and data collection system for epilepsy and seizure detection, and they investigated and proved the practicality of the new proposed device and methodology for data classification. Using the proposed smart bracelet, they gathered information from epileptics outside of the hospital. Following a seizure, the individuals were instructed to hit the mark button. To eliminate non-moving segments, the authors also introduced an automated extraction and annotation of moving segments technique. Next, they classified seizure and non-seizure movement segments using a two-layer ensemble model and Machine Learning (ML) techniques, achieving about 77% sensitivity and 97% accuracy in data classification. In [16], the authors investigated the detection of convulsive epileptic seizures using a single accelerometer sensor worn on the wrist. Three categories of convulsive seizures were included in the data set examined in this study: 1) psychogenic non-epileptic seizures, 2) generalized tonic-clonic seizures, and 3) complex partial seizures. The suggested system identified convulsive seizures lasting at least 10 seconds and only re-quired one accelerometer sensor. Accelerometer data from patients receiving video-electroencephalography monitoring—the gold standard for identifying epileptic seizures—was used to validate the suggested algorithm. To train Kernelized support vector data description, a new set of computationally efficient time domain features—including features extracted using a non-linear method—were utilized to classify seizure and non-seizure events, detecting roughly 87% of the three types of seizures. Using a tested seizure detection algorithm, in [17] the performance of two wearable devices based on electrocardiography and photoplethysmography is compared with a typical hospital Electrocardiogram (ECG). This algorithm categorizes seizures based on heart rate characteristics that are taken from the heart rate increase. The sensitivity reported in the article of wearable photoplethysmography (PPG) device, the hospital system, and the wearable ECG device are 32%, 57%, and 70%, respectively, concluding that wearable ECG performance is comparable to hospital ECG performance, however, seizure detection performance with the wrist-worn PPG device was significantly lower. On the other hand, the authors of [18] used a smartwatch to see if it might identify seizure occurrences in patients compared to continuous Electroencephalographic (EEG) monitoring for those admitted to an epilepsy monitoring unit. The selected neural network models for data classification were often able to detect seizure occurrences at an above-chance level, as evidenced by the patient-aggregated receiver operating characteristic curve's area under the curve of 0.58, even if the obtained overall low specificity implied a false alarm rate that would likely make the model unsuitable in practice.

The authors of [19] evaluated a Deep Learning (DL) approach to predict seizures in a statistically significant manner using multimodal wristband sensor data from several epileptic patients. They found that 43% of the patients had better-than-chance prediction using a leave-one-subject-out cross-validation technique. Analyses of time-matched seizure surrogate data showed that forecasting was not solely influenced by alertness state or time of day. When all sensor modalities were employed, prediction performance was maximized. It did not differ between focal and generalized seizure types, but it did typically improve with the size of the training dataset, suggesting that future work with larger datasets may yield even greater improvements. Also, a wrist-worn device was used to collect accelerometer data from patients in [20] for diagnostic evaluation of convulsive seizures. Specifically, K-means clustering and Support Vector Machine (SVM) were employed in an automated procedure to identify and categorize each seizure as either Epileptic Seizures (ES) or Psychogenic Non-Epileptic Seizures (PNES). Epileptology who were blinded to the accelerometer data compared the results with video EEG monitoring diagnoses. The results reported a sensitivity and specificity value for classifying ES from PNES of about 72.7% and 100%, respectively, whereas the positive and negative predictive values for classifying PNES were 81.3%

and 100%. The authors of [21] tested a wrist-worn smart device on children, adolescents, and young adults with various types of seizures in an epilepsy monitoring unit. Confirmation of seizure type and if there was rhythmic upper extremity jerking associated with the seizure was determined by a review of the video electroencephalograph. This was compared with the standard detection system of the considered commercial smartwatch, which detected only 16% of the total seizures, 31% of the generalized tonic-clonic seizures, and 34% of seizures associated with rhythmic arm movements. The main objective of the work proposed in [22] was to examine the features of motor manifestation during psychogenic nonepileptic seizures and convulsive epileptic seizures, as recorded by a wrist-worn accelerometer device. Finding quantifiable accelerometer characteristics that can distinguish between convulsive epilepsy and convulsive psychogenic nonepileptic seizures was the primary objective. Two new indices—tonic index and dispersion decay index — were used to quantify the Poincaré-derived temporal variations for every generalized tonic-clonic seizure and convulsive psycho-genic nonepileptic seizure event. The authors concluded that an automated classifier built using the features differentiated convulsive psychogenic nonepileptic seizure events with a sensitivity of about 95.5% and classified generalized tonic-clonic seizures with a specificity of 95%.

Van de Vel et al. [23] evaluated four different systems (including a smart mattress and a smart wrist device) based on efficiency, comfort, and user-friendliness and compared them to one patient suffering from focal epilepsy with secondary generalization. Despite nongeneralized and nonrhythmic motor seizures (involving only the head, having a tonic phase, or presenting primarily as sound) were frequently ignored, some of the devices had good results. In addition to its ease of use (few setup steps), comfort (con-tactless), and ability to customize patient-specific settings, the smart mattress was selected for the only selected patient for the experimentation stage. On the other hand, in [24] the development and validation of an Artificial Neural Network (ANN) model for automated detection of tonic seizures with visible clinical manifestation using a wearable wristband movement sensor (accelerometer and gyroscope) was reported. The dataset prospectively recorded for this study included 70 tonic seizures from 15 patients. An ANN model was trained to detect tonic seizures. The independent test dataset comprised nocturnal recordings, including 10 tonic seizures from three patients and additional (distractor) data from three subjects without seizures. The ANN model detected nocturnal tonic seizures with visible clinical manifestation with a sensitivity of 100%. Moreover, in another interesting work, accelerometer and electrodermal activity data captured by wrist-worn devices were used to create two multimodal automated convulsive seizure detectors [25]. The proposed algorithms were tested using a more varied data set than previous clinical studies, obtaining a much higher sensitivity (approximately 95%) when compared directly to the best state-of-the-art system using accelerometer and electrodermal activity. Most patients experienced less than one false alarm every four days, and 90% of patients experienced fewer false alarms than their seizure rate; no false alarms happened while they were at rest. Apart from detecting seizures, the algorithm demonstrated postictal autonomic dysfunction in 73% of cases and enabled accurate annotation of motor convulsion lengths. By a commercial wrist device, it was demonstrated in the study reported in [26] that PPG frequency showed an increase during pre- and post-seizure periods that was higher than the changes during seizure-free periods. Additionally, the PPG slope decreased during pre-seizure periods compared to seizure-free periods, and smoothness increased during the post-seizure period as compared to seizure-free periods. These results suggested to the authors that PPG analysis may offer additional information when monitoring patients with epilepsy. The study reported in [27] was among a few studies that evaluated and described extracerebral signal characteristics of various seizure types using a wrist-worn multimodal smartwatch. Based on the author's findings, Heart Rate (HR), Accelerometer data (ACC), and electrodermal activity were significantly elevated during seizures when compared with the baseline period during normal physical activities. However, only HR and ACC were independent predictors for overall seizures. Ge et al. [28] showed in another very interesting work how mobile devices might be used to track seizures and complete postictal surveys to find seizure triggers in a heterogeneous, nationwide population with epilepsy. 26% of all seizures were linked to different triggers, and 41% of participants who tracked seizures reported seizure triggers. According to persons with epilepsy in this study, stress was the most frequent cause of their seizures, followed by sleep deprivation and correlations with the menstrual cycle. However, many participants with seizure triggers noted that a combination of circumstances, most frequently stress and other factors like fatigue or lack of sleep, can cause seizures. This implied that these variables used together may change seizure thresholds and affect seizure timing and risk. A multicentre, in-home, prospective, video-controlled cohort study was proposed in [29], wherein people who had epilepsy intellectual disability, and nocturnal seizures were identified by movement or HR. Approximately 82% of the initial study participants completed the trial with the following results: median sensitivity per participant amounted to 86%, the false-negative alarm rate was 0.03 per night, and the positive predictive value was 49%, concluding that the combination of heart rate and movement resulted in reliable detection of a broad range of nocturnal seizures.

A very recent study assessed through a mixed methods design, the direct experiences of people with epilepsy independently using a non-invasive monitoring system named EEG@HOME, for an extended duration of 6 months, at home [30]. The study aimed to investigate factors affecting engagement, gather qualitative insights, and provide recommendations for future home epilepsy monitoring systems. The reported result showed the enthusiasm and aptitude of individuals with epilepsy for active health monitoring with new technology. From the conclusions, it emerged that independent home use of new non-invasive technologies can be made possible by remote training and assistance; nevertheless, to guarantee long-term acceptability and usability, systems must be incorporated into patients' daily routines, include healthcare providers, and give ongoing support and tailored feedback. The pilot study reported in [31], even if in a small cohort, has shown that seizure forecasting using a non-invasive wrist-worn multimodal sensor was much better than a random predictor for most patients tested. In an ambulatory scenario, wearable data was captured while engaging in regular activities, and seizure occurrences were concurrently validated by EEG. Of the six individuals examined, five had seizure forecasts that were noticeably more accurate than a random predictor, and seizure alarms in these five patients gave enough advance notice to enhance neuromodulation therapy or give fast-acting medicine. Xiong et al. [32] validated a forecasting method using multimodal cycles of epileptic activity recorded from commercial smart wrist devices. Here, seizure and heart rate cycles were extracted from 13 participants, investigating the relationship between seizure onset time and phases of seizure and heart rate cycles. The results of this study demonstrated that cycles detected from multimodal data can be combined within a single, scalable seizure risk forecasting algorithm to provide robust performance.

In the last article examined [33], a pilot study on the impact of quality of life for adolescents with epilepsy and their caregivers was described. Throughout the study period, there was a trend toward improvement in the overall quality of life measures of adolescents, as well as greater support for parental autonomy. According to the findings, adolescents with epilepsy and their caregivers were open to utilizing the commercial seizure detection device, despite certain restrictions with the SmartWatch. Moreover, according to the study's findings, seizure detection devices can help to live better reducing worry related to seizure safety and normalizing the natural developmental process of adolescents becoming independent of their families. The works discussed in this section are summarized in Table II.

TABLE II. OVERVIEW OF THE ARTICLES THAT INVESTIGATED EPILEPSY AND SEIZURE DETECTION THROUGH SMART WRIST DEVICES

	Commercial Device	Kind of smart wrist device	# end-users	Data Availability
[15]	no		N.A.	no
[16]	yes	Apple iPod touch	79	no
[17]	yes	Empatica E4	11	yes
[18]	yes	Fitbit Charge 2	40	no
[19]	yes	Empatica E4	69	no
[20]	yes	Apple Ipod touch	11	no
[21]	yes	SmartMonitor	41	no
[22]	yes	N.A.	79	no
[23]	yes	Epi-Care Free	1	no
[24]	yes	Epi-Care free	18	no
[25]	yes	Empatica E3 and E4	69	no
[26]	yes	Empatica E4	174	no
[27]	yes	Empatica E4	30	no
[28]	yes	Apple Watch	999	no
[29]	yes	Nightwatch	34	yes
[30]	yes	FitBit Charge 3,4,5	12	yes
[31]	yes	Empatica E4	6	no
[32]	yes	Fitbit	13	yes
[33]	yes	SmartMonitor	10	no

IV. CONCLUSION

This comprehensive review has meticulously examined the use of smart wrist devices for the detection of epileptic seizures, delving into its various dimensions and identifying both the challenges and opportunities that lie ahead for future research. Through a careful selection process, scientific publications relevant to the topic were analyzed, excluding many works considered inconsistent or with non-quality scientific content. An accurate analysis of the publication dates of the articles also demonstrates how there is a growing interest in the topic investigated, with analyzed works no older than 10 years. Overall, we have included an important number of publications in the present review, but many of these have been validated in controlled contexts, so they need further development and evaluation before implementation in clinical practice. We encourage collaboration within the field and reuse and improvement of already existing technological solutions, to prevent reinventions of the wheel and premature termination of development efforts.

ACKNOWLEDGMENT

We acknowledge co-funding from Next Generation EU, in the context of the National Recovery and Resilience Plan, Investment PE8 – Project Age-It: “Ageing Well in an Ageing Society”. This resource was co-financed by the Next Generation EU [DM 1557 11.10.2022]. The views and opinions expressed are only those of the authors and do not necessarily reflect those of the European Union or the European Commission. Neither the European Union nor the European Commission can be held responsible for them.

REFERENCES

[1] I. H. Willemse, S. Schootemeijer, R. van den Bergh, H. Dawes, J. H. Nonnekes and B. P. van de Warrenburg, “Smartphone applications for Movement Disorders: Towards collaboration and re-use,” Parkinsonism & Related Disorders, vol. 120, 105988, 2024.

[2] S. Vinciguerra and M. Vinciguerra, “Smart devices and healthy aging,” Nutrition and Healthy Aging, vol. 5, no. 1, pp. 13–19, 2019.

[3] K. Guk et al., “Evolution of wearable devices with real-time disease monitoring for personalized healthcare,” Nanomaterials, vol. 9, no. 6, p. 813, 2019.

[4] E. Beghi, “The epidemiology of epilepsy,” Neuroepidemiology, vol. 54, no. 2, pp. 185–191, 2020.

[5] C. E. Elger and C. Hoppe, “Diagnostic challenges in epilepsy: seizure under-reporting and seizure detection,” The Lancet Neurology, vol. 17, no. 3, pp. 279–288, 2018.

[6] Z. Chen, M. J. Brodie, D. Liew and P. Kwan, “Treatment outcomes in patients with newly diagnosed epilepsy treated with established and new antiepileptic drugs: a 30-year longitudinal cohort study,” JAMA Neurology, vol. 75, no. 3, pp. 279–286, 2018.

[7] B. Blachut, C. Hoppe, R. Surges, C. Elger and C. Helmstaedter, “Subjective seizure counts by epilepsy clinical drug trial participants are not reliable,” Epilepsy & Behavior, vol. 67, pp. 122–127, 2017.

[8] U. R. Acharya, S. V. Sree, G. Swapna, R. J. Martis and J. S. Suri, “Automated EEG analysis of epilepsy: a review,” Knowledge-Based Systems, vol. 45, pp. 147–165, 2013.

[9] E. Bruno et al., “Wearable devices for seizure detection: Practical experiences and recommendations from the

Wearables for Epilepsy And Research (WEAR) International Study Group," Epilepsia, vol. 62, no. 10, pp. 2307–2321, 2021.

[10] W. Li, G. Wang, X. Lei, D. Sheng, T. Yu and G. Wang, "Seizure detection based on wearable devices: a review of device, mechanism, and algorithm," Acta Neurologica Scandinavica, vol. 146, no. 6, pp. 723–731, 2022.

[11] S. Rheims, "Wearable devices for seizure detection: Is it time to translate into our clinical practice?" Revue Neurologique, vol. 176, no. 6, pp. 480–484, 2020.

[12] S. N. Grossman et al., "Rapid implementation of virtual neurology in response to the COVID-19 pandemic," Neurology, vol. 94, no. 24, pp. 1077–1087, 2020.

[13] S. K. Simblett et al., "Patients' experience of wearing multimodal sensor devices intended to detect epileptic seizures: a qualitative analysis," Epilepsy & Behavior, vol. 102, p. 106717, 2020.

[14] M. J. Page et al., "The PRISMA 2020 statement: an updated guideline for reporting systematic reviews," BMJ, vol. 372: n71, 2021.

[15] C. Dong et al., "A two-layer ensemble method for detecting epileptic seizures using a self-annotation bracelet with motor sensors," IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1–13, 2022.

[16] S. Kusmakar, C. K. Karmakar, B. Yan, T. J. O'Brien, R. Muthuganapathy and M. Palaniswami, "Automated detection of convulsive seizures using a wearable accelerometer device," IEEE Transactions on Biomedical Engineering, vol. 66, no. 2, pp. 421–432, 2018.

[17] K. Vandecasteele et al., "Automated epileptic seizure detection based on wearable ECG and PPG in a hospital environment," Sensors, vol. 17, no. 10, p. 2338, 2017.

[18] J. Mittlesteadt et al., "Evaluation of an activity tracker to detect seizures using machine learning," Journal of Child Neurology, vol. 35, no. 13, pp. 873–878, 2020.

[19] C. Meisel, R. El Atrache, M. Jackson, S. Schubach, C. Ufongene and T. Loddenkemper, "Machine learning from wristband sensor data for wearable, noninvasive seizure forecasting," Epilepsia, vol. 61, no. 12, pp. 2653–2666, 2020.

[20] V. D. Naganur, S. Kusmakar, Z. Chen, M. S. Palaniswami, P. Kwan and T. J. O'Brien,"The utility of an automated and ambulatory device for detecting and differentiating epileptic and psychogenic non-epileptic seizures," Epilepsia Open, vol. 4, no. 2, pp. 309–317, 2019.

[21] A. L. Patterson et al., "SmartWatch by SmartMonitor: assessment of seizure detection efficacy for various seizure types in children, a large prospective single-center study," Pediatric Neurology, vol. 53, no. 4, pp. 309–311, 2015.

[22] S. Kusmakar et al., "Novel features for capturing temporal variations of rhythmic limb movement to distinguish convulsive epileptic and psychogenic nonepileptic seizures," Epilepsia, vol. 60, no. 1, pp. 165–174, 2019.

[23] A. Van de Vel, K. Verhaert and B. Ceulemans, "Critical evaluation of four different seizure detection systems tested on one patient with focal and generalized tonic and clonic seizures," Epilepsy & Behavior, vol. 37, pp. 91–94, 2014.

[24] S. A. Larsen, D. H. Johansen and S. Beniczky, "Automated detection of tonic seizures using wearable movement sensor and artificial neural network," Epilepsia, vol. 65, no. 9, pp. e170–e174, 2024.

[25] F. Onorati et al., "Multicenter clinical assessment of improved wearable multimodal convulsive seizure detectors," Epilepsia, vol. 58, no. 11, pp. 1870–1879, 2017.

[26] F. Mohammadpour Touserkani et al., "Photoplethysmographic evaluation of generalized tonic-clonic seizures," Epilepsia, vol. 61, no. 8, pp. 1606–1616, 2020.

[27] W. Pipatpratarnporn, W. Muangthong, S. Jirasakuldej and C. Limotai, "Wrist-worn smartwatch and predictive models for seizures," Epilepsia, vol. 64, no. 10, pp. 2701–2713, 2023.

[28] A. Ge et al., "Seizure triggers identified postictally using a smart watch reporting system," Epilepsy & Behavior, vol. 126, p. 108472, 2022.

[29] J. Arends et al., "Multimodal nocturnal seizure detection in a residential care setting: a long-term prospective trial," Neurology, vol. 91, no. 21, pp. e2010–e2019, 2018.

[30] A. Biondi et al., "Feasibility and acceptability of an ultra-long-term at-home EEG monitoring system (EEG@ HOME) for people with epilepsy," Epilepsy & Behavior, vol. 151, p. 109609, 2024.

[31] M. Nasseri et al., "Ambulatory seizure forecasting with a wrist-worn device using long-short term memory deep learning," Scientific Reports, vol. 11, no. 1, p. 21935, 2021.

[32] W. Xiong et al., "Forecasting seizure likelihood from cycles of self-reported events and heart rate: a prospective pilot study," EBioMedicine, vol. 93, 104656, 2023.

[33] M. E. Thompson, J. Langer and M. Kinfe, "Seizure detection watch improves quality of life for adolescents and their families," Epilepsy & Behavior, vol. 98, pp. 188–194, 2019.

