1 Introduction

The estimated global prevalence of epilepsy is 50 million with approximately 5 million new cases diagnosed each year [1]. Of these, approximately 20–40% have refractory epilepsy, a version of the disease that is not controlled by typical antiseizure medications [2]. Generalized motor seizures and specifically generalized tonic–clonic seizures (GTCS) are considered one of the most dangerous seizure subtypes that are strongly associated with sudden unexpected death in epilepsy (SUDEP) [3]. Effective seizure detection and prediction systems are needed to give caregivers the opportunity to intervene at the proper time and prevent the dangerous consequences of a seizure. Electroencephalography (EEG) is the gold standard method for seizure detection [4] and prediction [5], however, it requires the use of either a hat/headset which is deemed uncomfortable and socially stigmatizing by epileptic patients [6]. This has driven research toward investigating the feasibility and effectiveness of alternative wearable and non-EEG systems in detecting and predicting seizure fits.

In addition to motor manifestations, several physiological measures can be discriminative of generalized motor seizures. These include electrodermal activity (EDA), muscle activity captured by surface electromyography (sEMG), and cardiovascular or respiratory measures obtained from electrocardiography (ECG) or photoplethysmography (PPG), such as heart rate (HR), heart rate variability (HRV), blood volume pulse (BVP), and oxygen saturation (SpO_2) [7, 8, 9, 10]. Further, detection of abnormal movement associated with seizures has been performed using accelerometers (ACC), yet motion signals obtained via ACCs exhibit relatively high false alarms when used alone due to other daily activities mimicking seizure-like movements [11]. This prompted the shift toward multimodal seizure detection systems, and the incorporation of other either motion-based sensors like gyroscopes (GYR) or the aforementioned physiological sensors.

For seizure prediction, a gold-standard signal has not yet been identified; therefore, progress in this area has been limited. Thus, the autonomic distinctions of the peri-ictal period remain an open research question, and ongoing studies are investigating how features derived from physiological signals can provide reliable predictive markers.

Accordingly, this scoping review aims to: (1) compare different modalities and algorithms used for seizures detection and prediction; (2) identify the most promising sensor combinations and approaches for both purposes; and (3) highlight current research gaps and limitations in this field. The findings of this review are intended to inform and guide future research toward the development of accurate, high-performance systems for the detection and prediction of GTCS.

2 Methodology

This scoping review was conducted in accordance with the PRISMA Extension for Scoping Reviews (PRISMA-ScR) guidelines [12] 1.

Conference papers and peer-reviewed articles of various study designs were included if they investigated wearable multimodal approaches for the detection or prediction of epileptic seizures. Studies were excluded if they (1) were review articles, (2) employed a unimodal detection system, (3) lacked clinical validation, or (4) targeted focal seizures only.

Three electronic databases (Scopus, IEEE Xplore, and PubMed) were searched until April 22, 2025 using Boolean operators, wildcards, and keywords relevant to epilepsy,

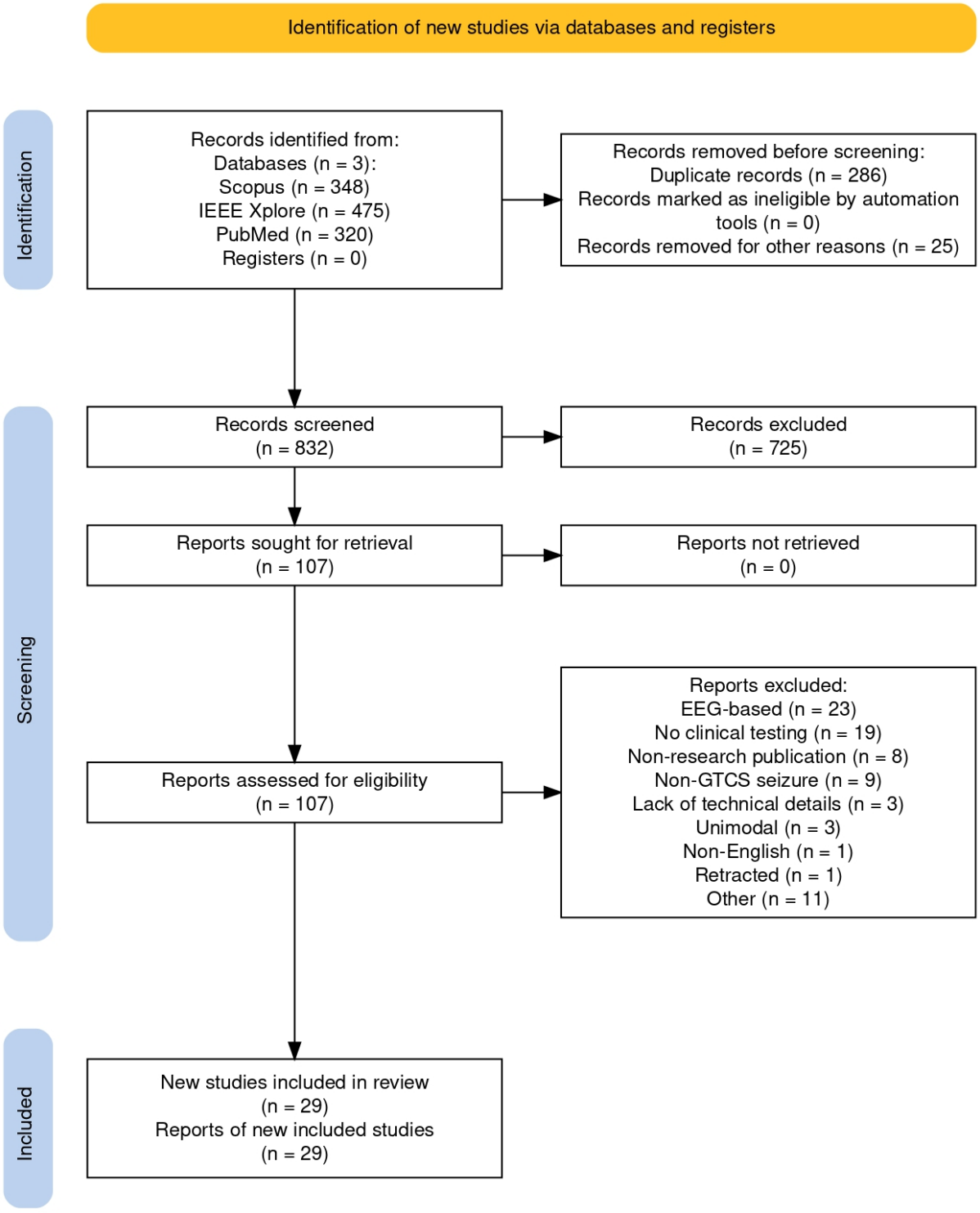

Figure 1: PRISMA Flow Diagram

wearable sensors, detection outcomes, and AI-based analysis. (supplementary file II).

After duplicates removal, retrieved articles were screened first by titles and abstracts, followed by reading through the full-text. Eight reviewers independently participated as pairs in screening. Screening decisions and record management were handled using Mendeley for reference organization and Google Sheets for collaborative screening.

Data charting was conducted in duplicate by independent reviewers using Google Sheets. No standardized or pre-piloted data extraction form was used; instead, reviewers extracted data deemed relevant to the review objectives based on team consensus. The following variables were systematically extracted from each included study: year of publication; task type (detection, prediction, or forecasting); study characteristics (clinical setting, average patient age, dataset size, targeted seizure types, and reference standard); device characteristics (wearability, commercial device name if applicable, and sensor placement); signal characteristics (sensor modalities, extracted biomarkers, and preprocessing steps); algorithm characteristics (task type, real-time applicability, patient-specific versus generalized model, and best-performing algorithm); and reported outcomes (performance metrics and key findings).

Extracted data were synthesized and presented using structured tables (Table S1, Table S2). Discrepancies during screening and data charting were resolved through collaborative discussion.

3 Results

A total of 26 studies, concerned with seizure detection, were included in this review (Table S1). These studies utilized a range of commercial and non-commercial devices for seizure detection. The most frequently used commercial device was the Empatica E4 (includes sensors for ACC, EDA, PPG, TEMP), which was tested in 15.4% of the studies [13, 14, 15, 16]. Additional studies employed either customized laboratory-developed devices or other commercial devices, such as: Shimmer [17, 18], Samsung SM-R800 watch [19], Mi-Microsoft wristband[20], Nightwatch [21], and Biovital P1 System [22, 23].

All included studies assessed various combinations of the following physiological and movement sensors and measures: ACC, BVP, GYR, sEMG, HR, HRV, SpO_2, EDA, ECG, and TEMP.

For seizure prediction and forecasting, three studies were found eligible [24, 25, 26] (Table S2). All three papers used the Empatica E4 wristband device for real-time data acquisition; however, the selected modalities for training and analysis differed among the papers.

3.1 Participants Demographics

3.1.1 Detection

Nine (34.62%) studies targeted generalized tonic-clonic and/or tonic-clonic seizures only [19, 27, 28, 29, 30, 31, 32, 33, 34]. Four (15.38%) studies focused solely on nocturnal seizures [17, 18, 29, 31].

Studies included either adults, pediatrics or a mixed population as follows: Five studies [19, 35, 36, 37, 38] focused solely on adults aged 20 [37] to 64 years [35]. From which, only one study provided the mean age [36], and another the mean and standard deviation [19]. Eleven out of 26 (42.3%) studies [13, 16, 18, 20, 22, 23, 27, 29, 30, 39, 40] were conducted

Table 1: Modalities (Detection)

Modality	Sensitivity	FAR/24H	Accuracy	Studies
ACC, GYR, sEMG, EDA	[81.69%–95.24%]	[0.64–1.21]	[93.16%–96.81%]	[22, 23, 28, 32, 40]
ACC, PPG	[80%–86%]	[0.2609–13.63]	—	[13, 16, 21, 38]
ACC, EDA, PPG	[93%–100%]	[0.08–2.339]	—	[15, 33]
ACC, ECG	[87%–92%]	—	—	[17, 39]
ACC, GYR	[76.84%–96%]	[0.98]	[97.28%]	[31, 41]
ACC, GYR, sEMG	[97%–100%]	—	—	[18, 34]
ACC, sEMG	[90.91%]	—	—	[27]
ACC, EDA	[93.9%–97.2%]	[0.53–1.8]	[96.7%]	[14, 30, 37]
ACC, ECG, sEMG	[90.9%]	—	—	[29]
ACC, ECG, EDA, sEMG	—	—	—	[36]
ACC, GYR, PPG	[87%]	[0.21]	[93%]	[19]
ACC, EDA, GYR, PPG	[89%]	[0.54]	—	[20]
EDA, PPG	[100%]	—	—	[35]

exclusively on pediatric patients aged between 1 month [20] and 17 years [39]. Among these, two studies [27, 29] did not specify exact age but indicated inclusion of children, while four provided both mean and median ages only [13, 16, 30, 40]. Ten studies [14, 15, 17, 21, 28, 31, 32, 33, 34, 41] included mixed-age populations, with age ranging from 2 [17] to 75 years [31], including two studies that did not specify the age range [15, 33]. In addition to seizure patients, five studies included control groups to test the performance of their seizure detection methods [17, 19, 28, 31, 34].

Sample sizes varied from 7 [29] to 166 participants [13] in studies involving children, and from 5 patients [38] to 36 [19] in studies including adults, and from 4 patients [32] to 135 patients [14] in the mixed-age population studies.

Twenty studies (76.9%) were conducted in inpatient settings, three studies in outpatient settings [28, 37, 41], and three were conducted in both settings [14, 15, 34].

3.1.2 Prediction and Forecasting

The three prediction studies were more uniform in the demographics of enrolled participants. The number of patients included in data acquisition ranged from 42 [24] to 139 [25], with mean ages ranged between 9.8 [26] and 14 [24] years, indicating a pediatric-dominant cohort. Two studies [24, 25] also included a control group (patients with no seizures) to differentiate seizure-related patterns from normal brain activity. All prediction studies were conducted in an inpatient setting.

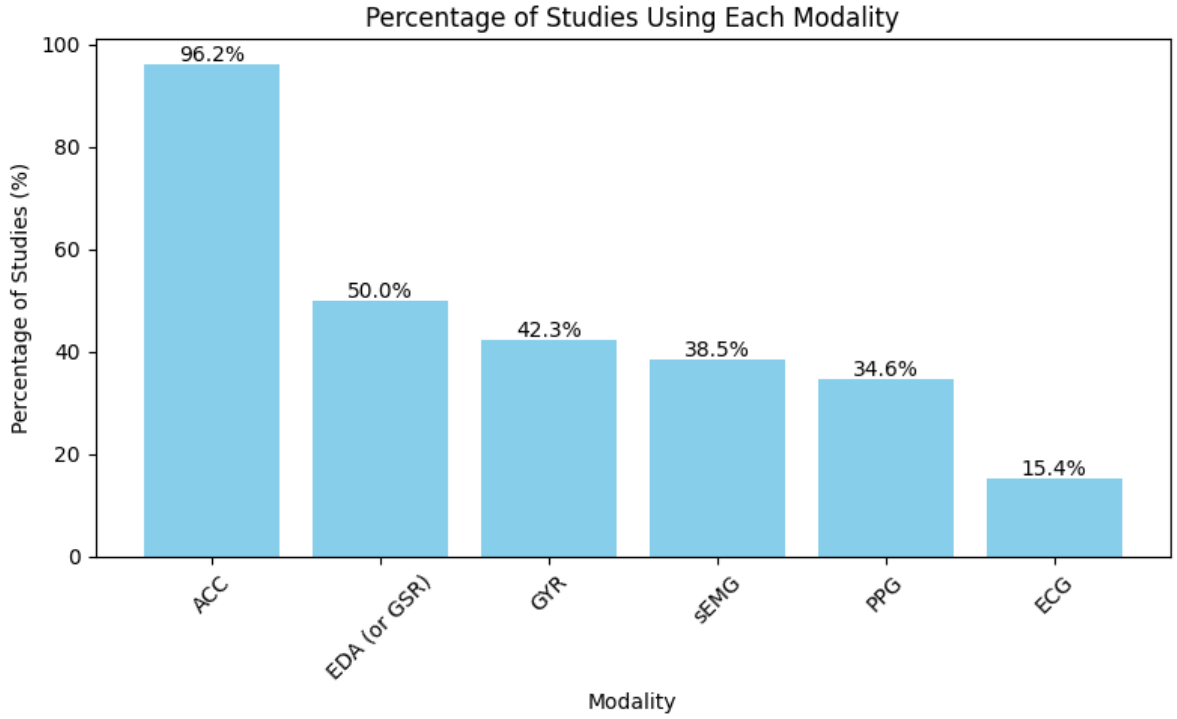

Figure 2: Percentage of Studies Using Each Modality. Please note that studies used multiple sensors, however, the combination is not shown in this graph

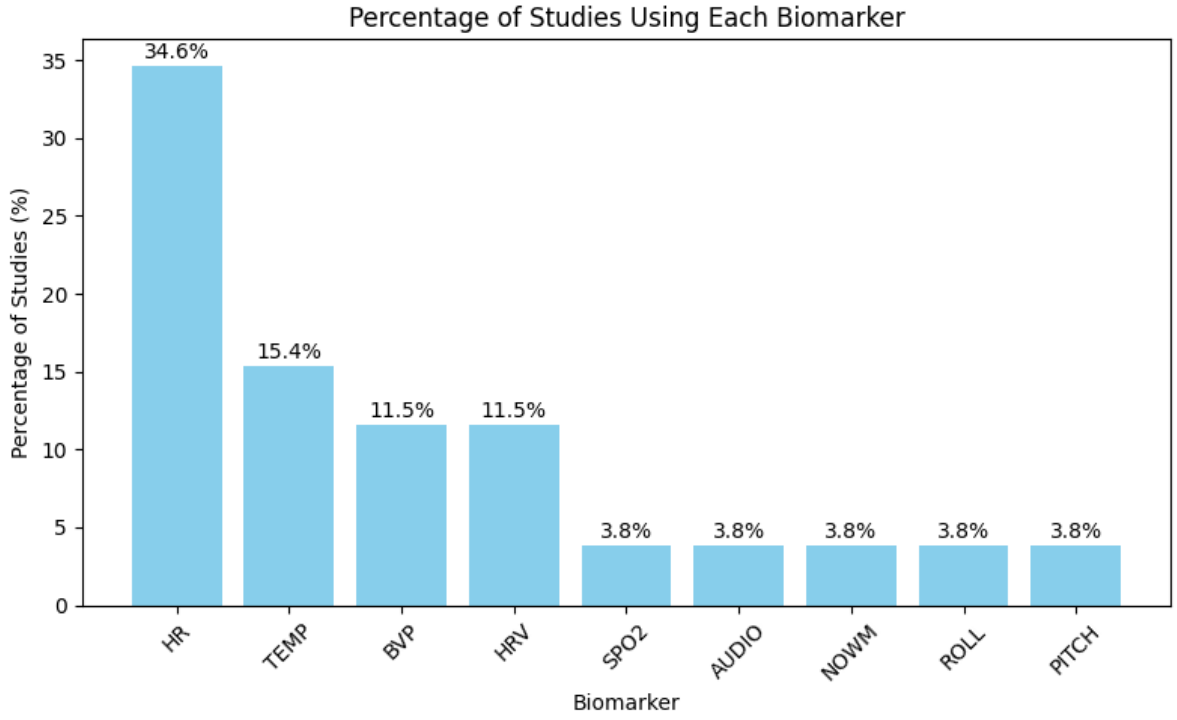

Figure 3: Percentage of Studies Using Each Biomarker

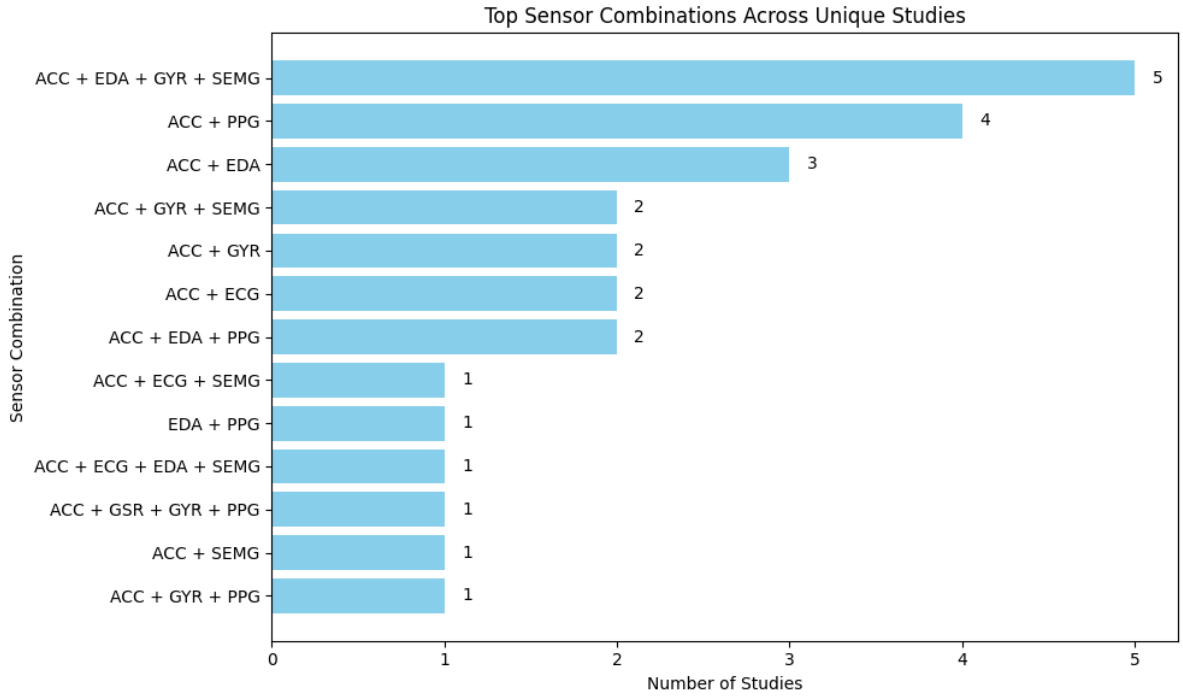

Figure 4: Frequency of Each Sensor Combination

3.2 Modalities

3.2.1 Detection

The most frequently used modality was ACC (96.2%) to capture the convulsive motor activity associated with tonic-clonic seizures. EDA followed as the second most used modality, appearing in half of the studies, while ECG was the least commonly used (15.4%) (Figure 2).

Several studies used raw sensor signals in addition to extracting specific biomarkers such as HR, HRV, BVP, and SpO2, which were then used as features in seizure detection models. HR was the most commonly used biomarker (34.6%), while SpO2, audio, Number of Wrist Movements (NOWM), a derived feature that summarizes hand and wrist movement frequency over time windows, and motion parameters such as PITCH and ROLL, which describe the orientation of the body/limb in the 3D space, were each used in only 3.8% of the studies (Figure 3).

Altogether, 13 different multimodal sensor combinations were reported (Figure 4). The most common was ACC + GYR + sEMG + EDA (19.2%). Almost all studies that directly compared unimodal and multimodal systems [13, 16, 22, 27, 29, 30, 32, 34, 36, 37, 39, 40] found that multimodal systems outperformed unimodal ones. The only exception was the study by Hegarty-Craver [39], where a cardiac algorithm using ECG alone achieved a lower false positive alarm (FPR) (1 per day) compared to ACC + ECG (2 per day). Additionally, for GTCS specifically, ACC alone outperformed other modalities and even multimodal combinations including PPG and EDA in two pediatric studies [13, 16].

The most commonly used multimodal sensor combination, ACC + GYR + sEMG + EDA [22, 23, 28, 32, 40] consistently achieved high performance (accuracy range: 93.16 % [40] – 96.81 % [22]), with the highest sensitivity (95.24%), accuracy (96.81%), precision (98.55) and lowest FAR/24h (0.64) reported by Wu et al. [22]. Among these studies,

Wang et al. [23] investigated the use of derived biomarkers (PITCH and ROLL, extracted from ACC and GYR) instead of or in combination with raw ACC and GYR data. They found that substituting ACC with PITCH or ROLL improved performance across all models (e.g. accuracy improved by approximately 2%), with the best results obtained using Support Vector Machine (SVM) classifier (when substituted with PITCH: Accuracy: 95.7%, Precision: 95.7%, Recall: 93.8%; With ROLL: Accuracy: 95.2%, Precision: 95.7%, Recall: 92.5%) compared to the original combination which achieved an accuracy of 93.4%, precision of 95.8%, and recall of 90.9%.

Another commonly used combination was ACC + PPG [13, 16, 21, 38]. Yu et al. [13] found that for generalized motor seizures, ACC + BVP achieved the best performance with a mean AUC-ROC of 0.805, whereas EDA performed worst with a mean AUC-ROC of 0.513. For tonic–clonic seizures specifically, ACC alone yielded the highest performance, with an AUC-ROC of 0.973, a sensitivity of 95%, and an FPR of 6.2%. Similarly, Tang et al. [16] reported that ACC alone performed best for tonic–clonic seizures (AUC-ROC of 0.995), while for seizure-type–agnostic classification, the fusion of ACC + BVP achieved superior results, with an AUC-ROC of 0.752. Another study, Arends et al. [21], in their in-home nocturnal cohort study, reported that their modality combination sensitivity was significantly high (median 85%) compared to a rhythmic movement-based bed sensor (median 21%). They further analyzed feature contributions and showed that HR was the critical modality for true positives (92%) and also for false positives, while ACC contributed only 8% of true positives and caused no false alarms.

ACC + EDA was also one of the top and high achieving combinations [14, 30, 37] with a reported highest sensitivity of 97.2% [37] and the lowest FAR/24h of 0.53 reported [14]. Their results validated Empatica's multimodal wristbands (E4 and Embrace) as reliable tools for GTCS detection in real-world and Epilepsy Monitoring Units (EMUs) settings. Chowdhury et al. [37] also reported that fusing ACC and EDA significantly improved classification accuracy (96.7%) and reduced FAR (unspecified) compared to unimodal approaches. Similarly, Poh et al. [29] reported that the overall performance was lower when only ACC features were included.

While most studies incorporate both physiological and motion-based sensors in their sensor combination modalities, 19.2% of the studies were purely motion-based, using sensor combinations of ACC + GYR [31, 41], ACC + GYR + sEMG [18, 34] and ACC + sEMG [27]. Among these, the ACC + sEMG + GYR configuration achieved the best performance with a sensitivity range of 97% [18]–100% [23].

In addition to studying their significance in seizure detection, a few studies have tested for the optimal sensor placement [27, 29], showing that using sensors on different body locations can reduce FAR and improve performance. Milosevic et al. [27] identified the left wrist (non-dominant hand) and right ankle as optimal positions for ACC sensors, while bilateral biceps were optimal for sEMG.

For details of the remaining reported combinations, refer to the supplementary file (S2).

3.2.2 Prediction and Forecasting

All three studies used EDA and PPG in their sensor combinations. One study additionally used ACC [26]. PPG was used to extract biomarkers like HR [24, 25], HRV [25], and BVP [26]. TEMP was also among the biomarkers used [25, 26], however, in one study [25], TEMP did not differentiate between seizure and non-seizure groups and was therefore not

included in further analysis. Vieluf et al. [24, 25] identified EDA and HR as containing sufficient seizure-predictive information, with reported performance of 62% sensitivity, and an accuracy range of 68–68.89%. These findings were further supported in the study of Vieluf et al. [25] , where HRV shown predictive value with patients with an impending seizure had lower HR and higher HRV compared to seizure-free patients in evening recordings. In the work of Meisel et al. [26], forecasting performance was highest when all modalities (EDA, BVP, TEMP, ACC) were combined achieving significant seizure forecasting (better-than-chance) in 43% of patients (30/69), where the mean sensitivity was 75.6%, the mean time in warning (TiW), the fraction of time spent in warning, was 47.2% and the mean prediction horizon was 31.6 minutes. Each modality contributed uniquely, though ACC sometimes reduced performance in worst-performing patients -defined as those for whom seizure forecasting accuracy wasn't significantly better than chance.

3.3 Preprocessing

3.3.1 Signal Synchronization and Quality Control

A fundamental preprocessing step reported in reviewed literature was the temporal alignment of data from wearable devices with a ground-truth reference, typically video electroencephalography (video-EEG), to ensure accurate event labeling. Four studies (15.3%) described specific synchronization methods [13, 16, 19, 21]. The reported techniques included manual clock synchronization at the start and end of recordings to correct for time drift [13], the use of a Network Time Protocol (NTP) for automated alignment [19], a three-step timing error compensation algorithm [16], and the synchronization of sensor data with event logs from video recordings [21].

Following synchronization, quality control was performed to ensure data integrity. Ten studies (38.5%) detailed their quality control procedures [13, 15, 16, 20, 21, 32, 34, 38, 39, 40]. A common strategy was the removal of data segments where the device was not worn. Two studies accomplished this using temperature data, excluding periods where sensed temperature fell outside a physiological range [13, 16]. Other methods involved trimming the initial and final 15 minutes of recordings to account for sensor calibration [13] or implementing signal-specific quality checks. For instance, heart rate data were only utilized if a signal quality index exceeded an 80% threshold [21], while data from segments with poor electrodermal activity (EDA) contact were discarded [32]. Other studies also reported using custom quality indices to clean data epochs before analysis [15, 34].

Furthermore, some protocols involved removing sliding windows with a high percentage (>60%) of missing data [20] or conducting manual reviews to identify and exclude recordings with failures or invalid annotations [13]. General artifact removal and signal cleaning were also explicitly mentioned in several other papers [38, 39, 40].

3.3.2 Noise and Artifact Removal

Majority of the studies (61.5%) reported applying specific signal processing techniques to remove noise and artifacts from the raw sensor data [13, 18, 19, 20, 22, 23, 27, 29, 32, 33, 34, 36, 37, 39, 40, 41]. Filtering was the most common approach, with techniques tailored to the specific signal modality. For accelerometer (ACC) and gyroscope (Gyro) data, band-pass filters were frequently used, with cutoff frequencies such as 1–24 Hz [22] or 0.2–47 Hz [29], to isolate movement patterns relevant to seizures. High-pass filters were

also applied to remove baseline drift or focus on significant movements [19, 27, 32, 34]. In addition to filtering, smoothing techniques like a five-point median filter [33] or a 3-second smoothing filter [35] were employed to reduce erratic signal fluctuations.

For other modalities, filtering strategies were similarly targeted. Surface electromyography (sEMG) signals were commonly processed with a high-pass filter (e.g., at 20 Hz) to remove motion artifacts and baseline noise [27, 29, 32] or a band-pass filter (e.g., 20-90 Hz) [22]. Electrodermal activity (EDA) signals were often smoothed using a mean or median filter to reduce noise [13, 23, 32]. Furthermore, a study reported the use of wavelet transformation for denoising multiple signal types, including heart rate (HR), EDA, and ACC [20], while others used notch filters to eliminate specific sources of interference like powerline noise [27, 36]. In the context of seizure prediction and forecasting, noise removal was also a noted preprocessing step. One study applied low-pass filtering specifically to the EDA signal to refine the data before analysis [24]. This highlights that while the ultimate goal (detection vs. prediction) differs, the foundational need to clean and denoise raw sensor signals remains a consistent and critical practice across the field.

3.3.3 Data Segmentation and Windowing

A nearly universal preprocessing step reported in the reviewed studies was the segmentation of continuous time-series data into fixed-length windows, a necessary step for feature extraction in most machine learning models. TThis technique was described in adequate detail in 69.2% of the detection studies [15, 19, 20, 22, 23, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 39, 41] and was also a key component of all of the 3 forecasting and prediction studies [24, 25, 26].

The duration of these windows varied considerably, often tailored to the physiological signals being analyzed. For capturing the rapid motor patterns characteristic of tonic-clonic seizures, shorter window sizes ranging from 2 to 6 seconds were frequently employed [22, 23, 27, 29, 33, 34, 35, 36, 41]. A 10-second window was also a common choice [15, 30, 31, 32]. While two studies used much larger segments, ranging from 5 to 7 minutes [19, 20].

Overlapping windows approach was implemented to ensure that seizure events occurring at the boundary of a window were not missed and to augment the volume of training data. The degree of overlap typically ranged from 50% [19, 23, 36, 41] to 90% [28, 31]. Overlaps of 75-80% were also frequently reported [20, 22, 27, 29, 30, 35].

All reviewed forecasting and prediction studies used different data preprocessing segmentation approaches. The segmentation strategies ranged from short, fixed-length epochs (30 seconds) and brief daily snapshots (15 minutes) to longer, seizure-centered windows (45 minutes). For example, one study [26] segmented continuous wristband sensor data into 30-second epochs, extracting features from each segment to train and evaluate their seizure forecasting model. Another study [25] utilized a single 15-minute autonomic recording taken in the evening (9:00–9:15 pm) as a fixed snapshot for seizure likelihood assessment, combining this with clinical data for prediction. In contrast, [24] applied segmentation of 45-minute preictal and interictal periods based on EEG seizure annotations, focusing on capturing nonlinear correlations between EDA and HR signals for unsupervised seizure prediction.

3.3.4 Class Imbalance Handling

A significant challenge inherent in seizure detection is the profound class imbalance between rare seizure events and the vast amount of non-seizure data. Of the seizure detection studies, 26.9% explicitly reported strategies to address this issue during model training [13, 15, 16, 19, 22, 28, 31]. No such methods were detailed in reviewed papers on seizure forecasting or prediction.

The most frequently cited technique was undersampling, where the number of normal non-seizure samples is reduced to create a more balanced dataset. Two studies employed random undersampling of non-seizure segments [13, 16]. A similar approach involved subsampling non-seizure epochs to achieve a specific, more manageable seizure-to-non-seizure ratio of 1:10 for training [19].

Conversely, other studies used oversampling or data augmentation techniques. One study reported using oversampling for seizure events, in combination with algorithmic class weighting, to increase the influence of the minority class [31]. Another study implemented a novel approach by applying a much higher (90%) overlap in its sliding window segmentation for seizure data, which effectively increased the number of seizure-labeled samples for training achieving seizure-to-non-seizure ratio of 1:1.5 [28]. These techniques are crucial for preventing machine learning models from developing a bias towards the majority (non-seizure) class and thereby failing to detect true seizure events.

3.3.5 Features Extraction

The extraction of features from the windowed signal data is a critical step. This process transforms the raw, time-series signals into a structured format suitable for detection algorithms. Feature extraction was explicitly detailed 17 of the detection studies [14, 18, 19, 22, 23, 27, 28, 29, 30, 31, 32, 33, 34, 36, 37, 40, 41] and was central to the methodologies of all three forecasting and prediction studies [24, 25, 26].

The extracted features spanned multiple domains. The most common were statistical and time-domain features, including measures like mean, variance, interquartile range, and the number of local maxima or zero-crossings [27, 29, 34, 41]. Frequency-domain features, derived from techniques like the Fourier transform or wavelet transforms, were also widely used [19, 29, 30, 37]. The number of features extracted varied significantly, from 19 [30] to 594 [31]. This process often involved deriving features from novel signals, such as attitude angles (pitch and roll), which were shown to be effective proxies or replacements for traditional accelerometer and gyroscope data [23].

Given the high dimensionality of the feature sets, several studies employed feature selection or dimensionality reduction techniques to identify the most salient predictors and reduce computational complexity. The methods reported include Principal Component Analysis (PCA) [37], statistical tests like ANOVA [41], T-tests [40], and the Wilcoxon rank-sum test [19], as well as machine learning-based approaches like Random Forest (RF) feature selection [33] and minimum Redundancy Maximum Relevance (mRMR) [40]. These techniques were shown to optimize the feature set, for instance by reducing 91 initial features to 71 [33], and ultimately improve classification performance [40].

In the context of forecasting and prediction, feature extraction was similarly vital but sometimes focused on different aspects of the physiological data. One study calculated Heart Rate Variability (HRV) metrics, specifically the root mean square of successive differences (RMSSD), to assess impending seizure likelihood [25]. Another forecasting approach extracted features from raw signals and their Fourier transforms as well as

incorporated non-physiological data such as signal quality indices and the time of day, creating a rich, 17-channel input for its model [26].

3.3.6 Normalization and Baseline Correction

Several studies incorporated normalization or baseline correction steps to account for inter-patient physiological variability and to standardize the input for detection algorithms. This process was detailed in seven of the detection-focused studies [15, 20, 23, 27, 35, 39, 40].

A common technique was the use of a moving baseline, where incoming data from a short window (e.g., 5 seconds) were compared against a constantly updated reference to detect sudden deviations indicative of a seizure [35]. A more personalized approach involved defining subject-specific baselines, for example, by using the median of a patient's signals over a period, and then calculating residuals from this baseline for analysis [20]. Other studies mentioned baseline correction or calibration as a general step for motion signals like ACC and GYRO [23, 40], or used high-pass filtering as an implicit method to remove baseline drift from ACC signals [27].

In addition to baseline correction, signal normalization or standardization was also performed. Normalization improved signal comparability between different people or recording sessions. Some studies used z-score normalization, which adjusts signals to have a mean of zero and a standard deviation of one [15, 39]. These procedures ensure that the scale of different signals and features does not unduly influence the model's performance and help in adapting the algorithm to individual physiological characteristics.

3.4 Algorithms

3.4.1 Deep Learning Methods

Studies have leveraged deep learning architectures to automatically learn hierarchical features and model complex temporal dependencies in multimodal sensor data. Deep learning methods were employed in 19.2% of the reviewed detection studies [13, 15, 16, 23, 31] and in 66.7% of the prediction studies [24, 26]. The most prominent architectures included Convolutional Neural Networks (CNNs) [13, 16], Long Short-Term Memory (LSTM) networks [13, 23, 26], and hybrid models combining both [13].

For the seizure detection task, hybrid CNN-LSTM models were shown to be particularly effective. One study identified a CNN-LSTM fusion model using accelerometer (ACC) and blood volume pulse (BVP) data as the best overall algorithm, achieving 83.9% sensitivity and a detection delay of 28 seconds across 28 seizure types [13]. For generalized tonic-clonic (GTC) seizures specifically, this model reached 95% sensitivity [13]. Standalone LSTM networks were also successfully applied, particularly for their ability to capture time-series dynamics. One such study demonstrated that an LSTM model with transfer learning significantly outperformed traditional learning, achieving 93% sensitivity for in-hospital motor seizures with a false alarm rate (FAR) of 2.3 per day [15]. Another study utilized an LSTM with attitude angle signals, among others, to achieve an accuracy of 83.4% [23].

Other neural network architectures were also explored. A CNN-based model was found to be feasible for detecting a broad variety of seizure types using ACC and BVP signals [16]. Simpler Artificial Neural Networks (ANNs) also proved effective, with one study reporting 100% sensitivity in detecting nocturnal tonic seizures in an independent test set

Table 2: Algorithms (Detection)

(a) Deep Learning and Personalized Algorithms

Algorithm	Studies	Real-time Analysis	Sensitivity	FAR	AUC-ROC
CNN	[13]	No	95%	—	0.769
	[16]		80%	13.63/24h	0.752
CNN + LSTM	[13]	No	83.9%	—	0.789
LSTM	[23]	Yes	—	8.46/24h	—
ANN	[31]	No	96%	0.23/Night	—
Transfer Learning[a]	[15]	—	67%	4.8/24h	0.97
Personalized Autoencoder[a]	[13]	No	100%	[0.0–95.36]/24h	—

All are inpatient studies.
[a]Algorithms with personalization.

(b) Ensemble Algorithms

Algorithm	Studies	Inpatient/ Outpatient	Real-Time Analysis	Sensitivity	FAR/24h	Accuracy
Random Forest	[28]	Outpatient	No	90%	1.21	—
	[19]	Inpatient		87%	0.21	93%
Bagged decision Tree Classifier	[37]	Outpatient	Yes	—	—	95.1%
XGBoost	[20]	Inpatient	Yes	80%	1.1	—
Two-Layer Ensemble Model	[41]	Outpatient	No	76.84% (Overall)	0.98 (Overall)	97.28% (Overall)
				94.57% (Overall)	0.46 (Night)	91.37% (Night)

Table 2: Algorithms (Detection) cont.

(c) Traditional Machine Learning Algorithms

Algorithm	Studies	Real-Time Analysis	Sensitivity	FAR/24h	Accuracy	AUC-ROC
SVM	[30]	No	88%	1.0	—	—
	[40]	No	87.13%	—	—	—
	[33]	Yes	—	0.08	100%	—
	[34]	No	100%	0.107	—	—
	[32]	No	81.7%	0.64	—	
	[27]	No	90.01%	—	—	—
KNN	[40]	No	88.16%	—	93.16%	—
LDA	[36]	No	—	—	—	0.914

All are inpatient studies.

(d) Rule-based and Threshold-based Algorithms

Studies	Real-Time Analysis	Sensitivity	FAR	Accuracy	AUC-ROC
[39]	Yes	92%	2.09/24h	—	—
[38]	Yes	85%	26.09%	—	0.8682
[21]	Yes	86%	0.25/Night	—	—
[17]	No	87%	6.3/Night	—	—
[35]	No	—	—	100%	—
[18]	No	97%	4%	—	—

All are inpatient studies.

[31]. In the context of personalization, an autoencoder model achieved 100% sensitivity for GTC seizures in select patients, although it was noted to be less scalable [13].

For the forecasting and prediction tasks, one study [26] employed LSTM neural networks trained using leave-one-subject-out cross-validation on continuously collected retrospective data. Another study [24] selected Deep Canonically Correlated Autoencoders (DCCAE) for training and validation, testing three different architectures: Fully Connected DCCAE (FC-DCCAE), Convolutional Neural Network DCCAE (CNN-DCCAE), and Gated Recurrent Unit DCCAE (GRU-DCCAE). Among these, GRU-DCCAE yielded the best clustering accuracy of 68.89%. Both studies lacked real-time implementation, relying instead on retrospective or offline data analysis.

3.4.2 Ensemble Methods

Ensemble learning, which combines multiple machine learning models to improve predictive performance, was a prominent and effective strategy in several detection studies. Ensemble classifiers were used in 23% of the detection studies including bagging, boosting, and more complex stacked architectures [19, 20, 22, 28, 37, 41]. Also, one forecasting study reported the use of random forest (RF) classifier [25].

For the seizure detection task, bagging-based methods, such as Random Forest (RF) and Bagged Decision Trees, were particularly common [19, 22, 28, 37]. One study demonstrated that algorithm achieved 90% sensitivity with a low false alarm rate of 1.21 per 24 hours for tonic-clonic seizures in a daily setting [28]. Another study found that a Bagged Decision Tree classifier, when applied to fused accelerometer (ACC) and electrodermal activity (EDA) data, yielded GTCS detection accuracey of 96.7% [37].

A more advanced approach was the Two-Layer Ensemble Method (TLEM), which stacked multiple base learners including RF, Extra Trees (ET), Gradient Boosting Decision Tree (GBDT), and AdaBoost (ADB) [41]. This stacked model was shown to outperform all of its single-layer components, achieving a particularly high sensitivity of 94.57% and a FAR of 0.46 per 24 hours for nocturnal seizures. While achieving a sensitivity of 76.84% and a FAR of 0.98 per 24 hours for overall, day and night, seizures [41].

For the seizure forecasting task, Vieluf et al. [25] evaluated the performance of seven supervised learning algorithms with RF achieving the higher accuracy of 68% and sensitivity of 62%.

3.4.3 Traditional Machine Learning

In detection, 30.8% of the studies reported the successful application of models such as SVM, K-Nearest Neighbors (KNN), and Linear Discriminant Analysis (LDA) [27, 29, 30, 32, 33, 34, 36, 40].

The most frequently and successfully implemented classifier was SVM [27, 29, 30, 32, 33, 34, 40]. One study found that an SVM delivered the best trade-off between accuracy and false alarms, achieving a 100% accurate recognition rate with just 0.08 false alarms per day [33]. Another study concluded that a linear SVM (SVM-L) provided the optimal sensitivity and overall performance among several tested models [34]. The effectiveness of SVMs was also noted when using attitude angle signals, where they yielded the highest overall accuracy compared to decision trees and LDA [23].

Other traditional classifiers also showed strong performance. KNN, particularly when using a cosine distance metric on features from four combined modalities, achieved a high sensitivity of 88.16% [40].

3.4.4 Rule-based and Threshold-based Methods

These methods rely on predefined physiological patterns or thresholds to trigger a seizure detection. This approach was used in 19.2% of the reviewed detection studies [18, 21, 35, 38, 39].

One study developed a system based on a multi-biosignal pattern, defining a seizure event as a sequence of HR increase, followed by a decrease in SpO_2, and a subsequent rise in electrodermal activity [35]. This rule-based method achieved an accuracy of 100% for seizure detection in GTCS patients [35]. Another study implemented a system with decision rules based on three factors: shaking, from an ACC, HR, and TEMP [38]. By classifying risk into discrete levels, the system achieved a sensitivity of 85% [38].

A threshold-based algorithm using cardiac physiological features was also reported, detecting 92% of seizures with tonic/clonic movements [39]. Another approach applied a Shewhart control chart with exponentially weighted moving averages to motion inertial and muscular activity, achieving a 97% detection rate with a 4% FAR [18]. A further study employed a combined accelerometry and heart rate threshold algorithm in a residential care setting, reaching a median sensitivity of 86% with a positive predictive value (PPV) of 49% [21].

3.4.5 Methods with Personalization

Recognizing the high degree of inter-patient variability in seizure manifestation, many studies investigated or recommended personalized algorithms. For detection studies, 30.8% highlighted the benefits of tailoring models to individual patients [13, 15, 20, 23, 27, 30, 36, 39].

One study showed that a "semi-patient-specific" approach, which included prior seizure examples from the test patient in the training data, improved sensitivity from 88% to 94% compared to a generic model [30]. Similarly, a personalized autoencoder was able to achieve 100% sensitivity for GTC seizures in certain individuals, a level of performance not reached by the generalized model [13]. A particularly effective technique was transfer learning, where a pre-trained general model was fine-tuned on patient-specific data. This method significantly improved performance, reducing the FAR from 11.3 per day with traditional learning to 2.33 per day [15].

Other studies underscored the need for personalization by observing that false alarms and key predictive features varied significantly between individuals [27, 36]. Some methodologies were inherently personalized, such as a system that tracked individual "physiomes" by establishing personal physiological baselines to detect seizure-related deviations [20].

4 Discussion

This scoping review provides an overview of the modalities and algorithms applied in seizure detection and prediction and highlights the most promising sensor combinations and approaches. These insights could guide future choices aimed at developing more accurate and high-performance systems for detecting and predicting generalized motor seizures, specifically GTCS.

4.1 Participants Demographics

4.1.1 Detection

While the reviewed studies were conducted on different populations and in different settings, several limitations still limit the generalizability of their results.

For instance, 76.9% of the reviewed detection studies (including all 11 pediatric studies), were conducted in an inpatient setting. While such settings allow for gold-standard seizure characterization via video EEG, they also restrict patients' range of movements and daily activities, which limits the applicability of the resulting models to real-world conditions. When tested in outpatient environments, these models often produce relatively higher FARs [14, 15, 28, 37]. However, studies like Poh et al. [30] tried to mitigate their inpatient bias by adding an extensive amount of real-world non-seizure data activity which allowed a more realistic estimation of the FAR.

Additionally, while there is no known standard for the minimum number of patients for non-EEG seizure detection, a dataset of at least 30 patients is needed so that the results are reproducible. 57.7% of seizure detection studies had valid data recordings from less than 30 patients [15, 21, 22, 23, 28, 29, 31, 32, 33, 35, 36, 37, 38, 40, 41]. And while adding control groups is recommended for achieving less false alarms, balancing data should be taken into account for better generalizability. For instance, one study [27] had a dataset 56 patients, out of whom, only 7 patients experienced tonic-clonic seizures and a control group of 49 patients.

This limitation in patient numbers significantly affects the performance of algorithms. For instance, Yu et al. [13] explored 4 different algorithms and the personalized Autoencoder was tested on a small subset limiting its generalizability, even though the total number of patients in the study was 166. Poh et al. [30] experienced a low number of seizures despite having many patients. Additionally, Larsen et al. [31] had a much smaller test set compared to its training set. Overall, these challenges highlight how the size and balance of patient datasets are critical factors in developing reliable seizure detection models.

4.1.2 Prediction and Forecasting

The reviewed prediction and forecasting studies were limited and involved only pediatric cohorts in inpatient settings. Given physiological and behavioral differences between pediatric and adult populations, these findings are not generalizable to adults without further validation. Further, despite substantial number of patients (a maximum of 139 patients) included in the datasets, more diverse datasets are necessary to validate and extend these results.

4.2 Modalities

4.2.1 Detection

Based on the 26 reviewed articles, it is apparent that non-EEG multimodal sensor configurations for detecting motor seizures are feasible and have a great promise compared to conventional detection and management methods.

It is important to note that direct comparison across the reviewed studies is challenging due to methodological heterogeneity, differences in study populations, and variability in training datasets. Nevertheless, the ACC + GYR + EDA + sEMG sensor combination

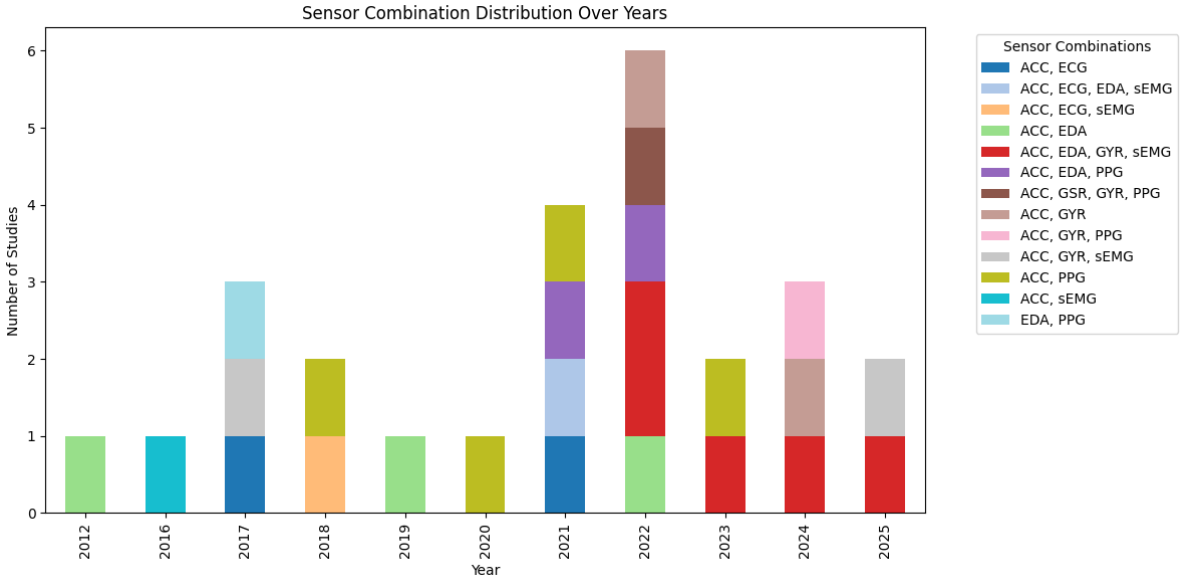

Figure 5: Sensor combination distribution over the years.

performance is consistently high across studies (table 1) regardless to the study setups. This may be because these setups combine the reliability of motion-based detection through ACC, GYR, and sEMG with the stabilizing contribution of physiological signals such as EDA, which helps reduce false alarms and enhance overall performance. Additionally, sEMG has been reported to rapidly detect seizures with notably low detection delay (11.7s) [29], highlighting its importance for timely intervention.

ACC + EDA is also one of the top performing combinations, with the advantages of less sensor modalities used to indicate less costs, more easier data pre-processing and signal fusion models. This is perhaps due to EDA's sensitivity to sympathetic activation which occurs closely with motor seizure onset consistent across multiple studies involving both children and adults [7], in addition to EDA being less sensitive to motion artifacts than other physiological signals like PPG for instance [42], making it more robust. Additionally, studies have demonstrated peri-ictal rises in EDA correlate with postictal generalized EEG suppression (PGES), a known SUDEP risk factor [14, 43], highlighting the potential of EDA in SUDEP prevention.

While this highlights the significance of EDA data in seizure detection, some studies have reported poor performance of EDA as a standalone modality and even when combined with other sensors such as PPG or ACC [13, 16]. This variability across studies stems perhaps from the age-related variability in EDA signals reported by the pediatric study [40], highlighting the need for algorithms trained on EDA to count for such variability.

Other physiological sensors such as PPG have also been widely used to extract biomarkers including HR [15, 19, 20, 21, 33, 35], HRV [19, 20], SpO2 [35], and BVP [13, 15, 16]. Among these, BVP in particular has shown strong potential, consistently achieving high performance across seizure types. This is consistent with findings from the observational clinical study conducted by Mohammadpour Touserkani et al. [44], where not only heart rate–dependent variables (frequency), but also other features of the PPG signal such as smoothness and slope were shown to vary relative to seizure timing. These additional PPG-derived features contribute to the improved ability of BVP-based detection algorithms to accurately identify seizures beyond the sole use of heart rate

metrics, highlighting the superior seizure discriminative information contained in BVP signals.

ECG has also been employed to derive HR [17, 29, 39] and HRV [39], with some studies reporting that unimodal ECG systems can achieve performance comparable to multimodal approaches [29, 39]. However, ECG w as used less frequently in the reviewed studies, largely due to its susceptibility to motion artifacts [17], its relative impracticality as a wearable sensor (requiring multiple electrodes to be placed on the chest or limbs), and the high inter-patient variability observed in cardiac-derived signals [17, 29].

Because of these limitations, ECG has mostly been used in nocturnal studies [17, 29]. This is relevant since SUDEP is more likely to happen at night [45], and HR and HRV are under investigation as potential SUDEP biomarkers [43]. Thus, ECG may serve a dual role in seizure detection and monitoring SUDEP-related autonomic changes.

Some studies have also investigated the use of non-traditional biomarkers for seizure detection, and interestingly, several of these have demonstrated detection capabilities comparable to, or even exceeding, those of more established biomarkers. Hamlin et al. [36] investigated the incorporation of audio features, derived from a MIC, in the detection system and reported that audio signals proved to be among the top ten features establishing separability between seizure and non-seizure data in four or five patients. Wang et al. [23] investigated the incorporation of attitude angle signals like PITCH or ROLL in their detection system and reported that in multimodal combinations, adding PITCH or ROLL alongside or replacing ACC, GYR outperformed combinations that excluded them across all models, as attitude signals were shown to have better anti-interference ability i.e. the attitude angle signals didn't show a wide range of energy enhancements compared to ACC and GYR in non-seizure periods. Instead of using raw ACC data, Xu et al. [33] used NOWM to distinguish seizure-like activity from normal daily movements.

In addition to the type of used modalities, sensor placement and signal quality were found to substantially impact detection performance. Tang et al. [16], for example, collected signals from different body parts, which introduced inconsistency in signal acquisition. Arends et al. [21] had to exclude individuals with abnormal movements or darker skin tones, as PPG signal quality was strongly affected by light intensity. Similarly, the chest-worn sensor used in Hegarty-Craver et al. [39] was not optimal for detecting limb movements, reducing the device's overall sensitivity. Cogan et al. [35] also reported issues of missing data during recordings caused by the SpO_2 sensor.

Thus, future studies should validate the incorporation of these biomarkers into detection systems, while also assessing optimal sensor placement. Evidence from [27, 29] shows that different sensor placements produce different outcomes, highlighting the importance of placement as a design consideration. In addition, studies should account for the variability exhibited by physiological signals across different populations by increasing and diversifying their cohorts, and by developing personalized models for highly patient-dependent modalities such as HR and HRV.

4.2.2 Prediction and Forecasting

Although the tasks and methodological scopes of the three studies varied, together they provide strong evidence for the feasibility of using wearable data from the Empatica E4 wristband in combination with machine learning or deep learning algorithms for seizure prediction and forecasting. Vieluf et al. [24, 25] demonstrated that the purely autonomic sensor set of EDA and PPG (from which HR and HRV are derived) could successfully

discriminate pre-ictal periods in a substantial proportion of patients in their cohorts. However, the highest prediction performance was reported by Meisel et al. [26], where all available sensor modalities on the E4 device (EDA, PPG/BVP, ACC, and TEMP) were incorporated into the forecasting models, confirming the superiority of multimodal combinations demonstrated in detection studies.

Biomarkers derived from PPG appear to be the primary seizure detectors, and while two studies [24, 25] proposed HR information to have seizure predictive information, the observational clinical study by Mohammadpour Touserkani et al. [44] show that frequency, smoothness, and slope change during the peri-ictal and post-ictal phases of a seizure, indicating that raw PPG signals may provide additional information regarding usability of these signals for seizure prediction. Future studies should test raw PPG signals instead of its derived biomarkers in larger and more diverse cohorts.

4.3 Preprocessing

The preprocessing pipeline across the reviewed studies reveals a consistent, multi-stage approach to preparing wearable sensor data for analysis. The initial steps of synchronization and quality control are fundamental for ensuring data integrity, yet there is a notable lack of a standardized protocol. While methods ranging from manual clock alignment [13] to automated NTP [19] were reported, the reliance on manual or semi-automated processes can be labor-intensive, prone to human error and represents a barrier to the seamless, large-scale deployment of these systems. Future work should focus on developing fully automated and robust algorithms for real-time signal quality assessment and data synchronization.

Following quality control, the application of filtering techniques was nearly universal, with methods appropriately tailored to specific signal modalities, such as band-pass filtering for motion sensors [22, 29] and high-pass filtering for sEMG [27]. The primary challenge in this stage is the trade-off between noise reduction and the preservation of subtle, seizure-relevant physiological signatures. Similarly, the segmentation of data into windows is a critical design choice that directly influences model performance. The literature showed a clear distinction, with shorter windows (2-10s) used for capturing the rapid dynamics of motor seizures [27, 31] and longer windows (>30s) used for forecasting or analyzing slower autonomic changes [20, 26]. The optimal window size and overlap remain an open question and may require patient-specific or context-aware adaptation.

The pervasive issue of class imbalance was addressed with various strategies, primarily under- and over-sampling [13, 16, 31]. While effective, simple random undersampling risks discarding valuable information from non-seizure periods, which could be crucial for building robust models that can distinguish seizures from vigorous daily activities. More advanced methods, such as synthetic data generation or cost-sensitive learning algorithms, were not widely reported and represent a significant area for future research. Finally, the use of feature engineering and subsequent selection [33, 40] versus the end-to-end learning approach of deep learning models marks a key divergence in methodology. While hand-crafted features offer interpretability, the trend towards deep learning suggests a move to reduce reliance on domain-specific feature design. Normalization and baseline correction [15, 20] were identified as crucial steps for personalization, enabling models to adapt to the significant physiological variability among individuals.

4.4 Algorithms

The reviewed literature demonstrates wide methodological diversity in algorithms for GTCS detection, prediction, and forecasting, ranging from interpretable rule-based systems to advanced deep learning architectures. For detection, Artificial Neural Networks (ANNs) have shown particular promise, with Larsen et al. [31] achieving 100% sensitivity and a FAR of 0.16 per night in nocturnal seizure detection. While CNN and hybrid CNN-LSTM models have been explored, their higher FPR remain a barrier to clinical translation [13, 16]. Ensemble methods such as the Multi-Level Dynamic Time Pile (MLDTP) framework [22] and traditional classifiers like Support Vector Machines (SVMs) [30] also demonstrate strong performance, particularly when validated against real-world non-ictal data. Simpler threshold- and rule-based algorithms provide interpretable, real-time solutions, exemplified by the cardiac-based detector of Hegarty-Craver et al. [39], though their limited adaptability reduces applicability across diverse patients.

In forecasting, supervised recurrent neural networks, especially Long Short-Term Memory (LSTM) models, are the dominant approach. Meisel et al. [26] reported significant forecasting in 43.5% of patients without requiring patient-specific data or dependence on seizure type, suggesting broader generalizability than previously assumed. In contrast, Nasseri et al. [46] achieved forecasting in 83% of focal epilepsy patients, highlighting both the potential of LSTMs and the need to validate generalization across seizure types. Beyond supervised learning, unsupervised methods such as Deep Canonically Correlated Autoencoders (DCCAE) [24] demonstrate the ability to extract predictive features from multimodal physiological signals without labeled seizure events, offering a path forward for wearable-based forecasting where annotation is limited.

A consistent challenge across detection and forecasting is the limit number of available studies and the high inter-patient variability. While some architectures appear capable of patient-independent generalization, many models fail to provide reliable performance across all individuals. Personalization strategies, such as transfer learning [15] or integration of clinical information [25], have shown promise in improving model robustness, most notably through reductions in false alarm rates and better adaptation to individual physiological profiles.

Overall, while advanced deep learning and ensemble methods have achieved encouraging results, no single algorithm yet combines the sensitivity, low FAR, generalizability, and real-time capability required for clinical adoption. Future progress should target balancing generalizable architectures with personalized adaptation, and validating algorithms in real-world ambulatory settings to ensure reliability and safety in real-world.

4.5 Strengths and Limitations

This scoping review followed a rigorous methodology to identify and chart relevant studies, with a focus on promising modalities, features, and algorithms that may inform future research.

However, a few limitations exist: Only studies published in the English language were reviewed. Further, studies demographic characteristics were heterogenous and sample size in some studies was small which may limit their generalizability to real world settings. Moreover, in this review, description of study methodology and results were given, however, we did not attempt to assess the quality and robustness of included studies.

Another key limitation is that only 26.9% of the detection studies [20, 21, 23, 29, 37, 38, 39], and none of the prediction and forecasting studies performed real-time data analysis

highlighting a critical gap between experimental research and practical application.

Finally, the optimal timing and duration for data recording in seizure prediction remain unclear. Although a time interval of 9:00 to 9:15 pm was hypothesized to be ideal for predicting seizures that could occur during nighttime or early morning hours [25], which are especially important, particularly for pediatric patients, as nighttime supervision can help reduce the risk of sudden unexpected death in epilepsy (SUDEP) [47], it is necessary to identify the shortest data windows that still enable reliable prediction across different patient groups to improve model accuracy and reliability

5 Conclusion

Non-EEG seizure detection and prediction hold great promise for improving the quality of life of people with epilepsy. Combining EDA with motion sensors such as ACC, sEMG, and GYR has proven to be a reliable approach for seizure detection, while PPG data has emerged as a primary seizure predictor. Several advancements have been made in the field of seizure detection, though more outpatient validation is required for clinical implementation.

On the other hand, a clear research gap is present in the field of seizure prediction and forecasting. More work is needed to establish reliable peri-ictal biomarkers, validate algorithms across diverse populations, and translate prediction models into practical, patient-centered applications.

In this review, we presented, assessed and compared seizure detection and prediction/forecasting studies, highlighting the most promising sensor combinations and algorithmic approaches while also identifying current limitations.

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