SPWID 2025

The Eleventh International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems

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SPWID 2025 Editors

Steve Chan, VTIRL, VT/DE-STEA - Orlando, USA

SPWID 2025

Forward

The Eleventh International Conference on Smart Portable, Wearable, Implantable and Disability-oriented Devices and Systems (SPWID 2025), held between April 6th, 2025, and April 10th, 2025, in Valencia, Spain, continued a series of co-located events bridging the concepts and the communities dealing with specialized implantable, wearable, near-body or mobile devices, including artificial organs, body-driven technologies, and assistive services.

Mobile communications played by the proliferation of smartphones and practical aspects of designing such systems and developing specific applications raise particular challenges for a successful acceptance and deployment.

We take here the opportunity to warmly thank all the members of the SPWID 2025 technical program committee, as well as all the reviewers. The creation of such a high-quality conference program would not have been possible without their involvement. We also kindly thank all the authors who dedicated much of their time and effort to contribute to SPWID 2025. We truly believe that, thanks to all these efforts, the final conference program consisted of top-quality contributions. We also thank the members of the SPWID 2025 organizing committee for their help in handling the logistics of this event.

We hope that SPWID 2025 was a successful international forum for the exchange of ideas and results between academia and industry for the promotion of progress in the area of smart portable, wearable, implantable and disability-oriented devices and systems.

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Remote Photoplethysmography System for Vital Signs Estimation: Perceived Usability Evaluation by Elderly People

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***Abstract*— Remote photoplethysmography has emerged as a promising continuous, non-invasive vital signs monitoring technique. This technique provides real-time estimation of key vital signs, including blood oxygen saturation, breathing rate, and heart rate, by analyzing a video of the user's face. To assess perceived usability, elderly end-users and related caregivers completed the System Usability Scale and the short version of the User Experience Questionnaire, providing quantitative scores and qualitative feedback on usability, reliability, and satisfaction. The results demonstrate the robustness and user-friendliness of the system, particularly for caregivers, suggesting some refinement to make it more accessible to older users.**

Keywords- Remote Photoplethysmography (rPPG); Contactless Health Monitoring; Vital Sign Estimation; Usability Evaluation; System Usability Scale (SUS); User Experience Questionnaire (UEQ).

I. INTRODUCTION

Continuous monitoring of vital signs plays a key role in preventing various heart and respiratory system diseases. Heart Rate (HR), Breathing Rate (BR), and blood oxygen saturation (SpO_2) are critical indicators for assessing the state of human health. While wearable devices such as smartwatches have gained widespread popularity, contactless systems have seen increased adoption, particularly following the COVID-19 pandemic [1]. In recent years, researchers have investigated remote photoplethysmography (rPPG), a non-contact technique that analyses subtle variations in skin color caused by blood fluctuation in peripheral vessels [2]. These color variations are due to periodic changes in blood volume linked to the cardiac cycle, which can be extracted from Red-Green-Blue (RGB) video signals using signal processing and filtering techniques. The rPPG method typically involves face detection, Region-Of-Interest (ROI) selection, signal decomposition, and post-processing to estimate heart rate, breathing rate, and blood oxygen saturation with high accuracy [3]. This technology enables non-invasive vital signs monitoring by analyzing video data of the user's face acquired using consumer devices, such as RGB or smartphone-integrated cameras, which are low-cost and extremely diffused [4]. This innovation offers substantial promise for remote health monitoring, especially within telemedicine applications. Ensuring usability is essential to make health monitoring solutions practical, efficient, and accessible in real-world scenarios. Usability and acceptability are particularly critical for adopting systems, such as rPPG, especially among older adults, as they strongly influence engagement and sustained use [5]. This paper examines the experimental development phase of the proposed solution, focusing on usability outcomes, feedback on sustainability, and its potential integration into services and interventions designed for aging populations. The structure of the paper is as follows: Section II outlines the materials and methods used, detailing the device under usability investigation, as well as the protocols and questionnaires used for user experience data collection; Section III presents the findings related to usability and discusses the obtained results, while Section IV provides conclusion and future works.

II. MATERIALS AND METHODS

This section provides an overview of the rPPG system employed in the study followed by an introduction to the basic concepts of usability and a description of the questionnaires used to evaluate the user experience in this research.

A. Hardware and Software Description

Remote photoplethysmography (rPPG) allows the monitoring of vital signs using only a vision sensor and a processing unit. Most studies use consumer webcams or cameras connected to PCs to capture the video stream of the user's face. In our system, the NexiGo N960E webcam (Figure 1a) was selected for facial video acquisition since the built-in light ring ensures optimal signal quality even in low-light conditions (three adjustable brightness levels) and the Raspberry Pi 4 Model B was selected as the processing unit due to its efficiency and cost-performance ratio (Figure 1b), as evidenced in [6]. The input of the algorithmic pipeline for vital signs estimation is a video stream taken by the selected webcam. As detailed in [6], the pipeline consists of two main stages: (1) the pre-processing stage and (2) the feature extraction and vital signs estimation stage.

The system was tested in a controlled environment to assess its accuracy. The experiment involved measuring vital signs at various distances from the user to the camera, using data collected by certified devices for ground truth.

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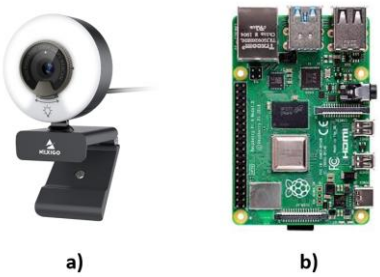

a) b)

Figure 1. (a) NexiGo N960E Webcam and (b) Raspberry Pi 4 Model B.

Different kinds of metrics were proposed in this research area for evaluating vital signs measurement methods. Here, the commonly used Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) metrics were utilized. At 0.5m, the system demonstrated accurate HR estimation with a MAE of 2.20 and an RMSE of 3.96. Similarly, the best results for BR were achieved at 0.5m, with a MAE of 1.80 and an RMSE of 2.15. For SpO_2 estimation, the average percentage difference from ground truth increased with distance, with the lowest error (0.85%) at 0.5m. Performance declined as distance increased, emphasizing optimal accuracy at closer proximity. The experiment was conducted in a controlled environment to ensure optimal lighting and positioning. However, real-world conditions may introduce factors such as variable lighting, background noise, and user movement, which could affect both the accuracy of rPPG measurements and overall usability.

The Graphical User Interface (GUI) was designed to be intuitive. Figure 2 illustrates the GUI that caregivers and elderly users interacted with. In the upper-left corner, a live feed from the webcam is displayed, assisting users in correctly positioning their faces for capturing. Once the acquisition is completed, the estimated vital signs are displayed in the upper right corner (green box). In addition, there is a section (black box) for manual entry of parameters from certified devices. Under this area (red box) any messages about data transmission or connection errors are displayed. Below the data transmission area, a countdown timer, set to 30 seconds, informs the user of the remaining acquisition time. Since the graphical user interface is entirely in Italian, Figure 3 shows for clarity a translated English version of the interface, created specifically for dissemination purposes and not presented to users.

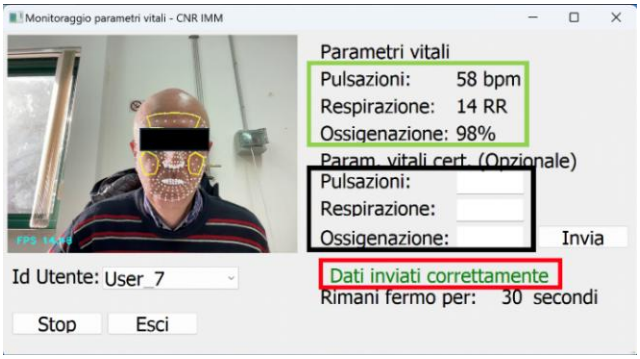

Figure 2. Graphical User Interface of the rPPG system, Italian version.

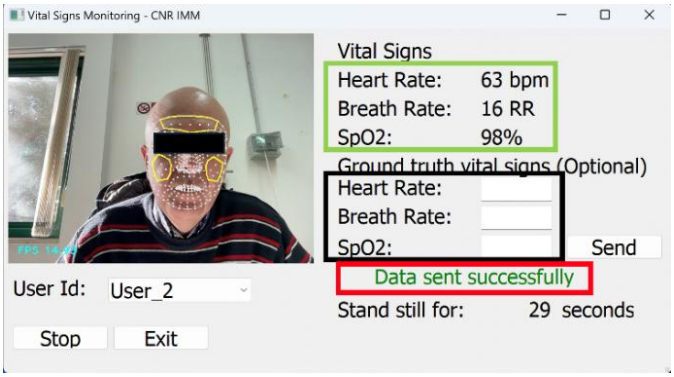

Figure 3. Graphical User Interface of the rPPG system, English version.

B. *Usability Rules and Protocols*

Usability measures how easy and intuitive a software product, website, application, or interactive system is for users. Two widely accepted definitions of usability come from Jakob Nielsen and ISO 9241-11. Nielsen describes usability as a quality attribute that evaluates ease of use and includes components such as learnability, efficiency, memorability, error reduction, and satisfaction. He proposed ten general heuristics to guide User Interface (UI) design, focusing on accessibility and intuitiveness [7]. Usability principles have been widely studied since the foundational works of Nielsen, and more recent studies have further explored their applications in digital health technologies [8].

The ISO 9241-11 standard defines usability as "the extent to which a system, product or service can be used by specific users to achieve specific goals with effectiveness, efficiency, and satisfaction in a defined context of use" [9]. Usability evaluation typically combines quantitative approaches, such as standardized questionnaires and metrics, with qualitative methods like interviews and observations to provide deeper insights into user behavior and preferences. For decades, practitioners and researchers in user-centered design and Human-Computer Interaction (HCI) have had a strong interest in the measurement of perceived usability [10].

A key tool for measuring perceived usability is the System Usability Scale (SUS), developed in the 1980s. The SUS is a 10-item questionnaire where participants rate each item on a 5-point Likert scale. The resulting score, ranging from 0 to 100, offers a quick and reliable assessment of usability and is especially useful for benchmarking systems [11]. Table 1 provides the full list of SUS items.

Another widely used tool is the User Experience Questionnaire (UEQ) which provides a more detailed assessment of usability dimensions. This questionnaire examines specific aspects such as reliability, intuitiveness, and satisfaction, offering a nuanced perspective on user perceptions. The standard UEQ includes 26 items, taking 3–5 minutes to complete, while its short version (UEQ-S) comprises only 8 items, making it suitable for constrained circumstances. The UEQ-S Questionnaire has been employed in this study to complement the SUS. It evaluates

two main dimensions: Pragmatic Quality (PQ), focused on usability and efficiency, and Hedonic Quality (HQ), related to attractiveness and emotional engagement [12]. The decision to limit the analysis to these dimensions aligns with the UEQ-S structure and ensures a focused assessment of the system's perceived usability and user experience. The UEQ-S uses a 7-point bipolar scale, ranging from -3 (extremely negative) to +3 (extremely positive), with 0 indicating neutrality. This balanced scale effectively captures both positive and negative feedback. Key pairs in the scale include "Confusing – Clear," "Complicated – Easy" (PQ), and "Boring – Exciting," "Uninteresting – Interesting" (HQ), which evaluate how users perceive the system's functionality and its emotional impact. Table 2 lists the items included in the UEQ-S.

TABLE I. SYSTEM USABILITY SCALE (SUS) ITEMS.

	SUS items
1.	I think that I would like to use this system frequently.
2.	I found the system unnecessarily complex.
3.	I thought the system was easy to use.
4.	I think that I would need the support of a technical person to be able to use this system.
5.	I found the various functions in the system were well integrated.
6.	I thought there was too much inconsistency in this system.
7.	I would imagine that most people would learn to use this system very quickly.
8.	I found the system very cumbersome to use.
9.	I felt very confident using the system.
10.	I needed to learn a lot of things before I could get going with this system.

TABLE II. SHORT VERSION OF THE USER EXPERIENCE QUESTIONNAIRE (UEQ-S) ITEMS.

	UEQ-S items	
Obstructive	-3 -2 -1 0 +1 +2 +3	**Supporting**
Complicated	-3 -2 -1 0 +1 +2 +3	**Easy**
Inefficient	-3 -2 -1 0 +1 +2 +3	**Efficient**
Confusing	-3 -2 -1 0 +1 +2 +3	**Clear**
Boring	-3 -2 -1 0 +1 +2 +3	**Exiting**
Not Interesting	-3 -2 -1 0 +1 +2 +3	**Interesting**
Conventional	-3 -2 -1 0 +1 +2 +3	**Inventive**
Usual	-3 -2 -1 0 +1 +2 +3	**Leading**

The short version of the UEQ (UEQ-S) was chosen over the more recent UEQ+ because it allows for a rapid yet reliable evaluation of user experience while minimizing cognitive load for elderly participants. Given the target population's limited familiarity with technology, a more extensive questionnaire could have impacted response quality and completion rates. The UEQ-S retains the core dimensions of usability and user engagement, making it well-suited for our study's goals.

III. RESULTS

The usability and acceptability of the rPPG system were tested in two elderly care facilities, involving 27 participants: 20 beneficiaries (age 65-85, with a mean age of 74.5 years) with varying levels of education and low to moderate familiarity with technology, and 7 staff members (age 30-55), mainly nurses and care assistants with greater technological proficiency. Training sessions were conducted to ensure the correct use of the device and accurate data collection procedures. During the experiment, the camera and computer were positioned in a controlled environment with optimal lighting and seating conditions. SUS and UEQ-S tests were completed by both the elderly beneficiaries and the nursing home staff. The results of the perceived usability evaluation are detailed below.

Table 3 provides the average scores for each item of the SUS questionnaire by users and staff during trials. The scores for each item are then transformed: for odd-numbered items, 1 is subtracted from the response, and for even-numbered items, the response is subtracted from 5. The transformed scores are then summed and multiplied by 2.5 to obtain a score ranging from 0 to 100.

TABLE III. SUS SCORES.

Item	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**Scores**
Users	5	1	5	5	5	1	4	4	5	1	**80.0**
Staff	5	1	5	1	5	1	4	1	5	1	**97.5**

A SUS score of 68 is widely considered to be the benchmark for good usability, based on extensive research and studies of SUS interpretation. The SUS evaluation revealed a notable difference between the two user groups. Employees gave an average score of 97.5, reflecting their perception of the system as exceptionally easy to use and well-suited to their professional needs. This high score underscores the functionality, reliability, and user-friendly design of the rPPG system, which fits well with the workflow requirements of trained professionals.

In contrast, users gave a lower average score of 80. While this score still indicates good usability, it also indicates minor difficulties experienced by non-professional elderly users. These challenges are mainly related to specific items, such as the need for technical support and system comfort (items 4 and 8), maybe due to differences in technological familiarity and user expectations. It could also be due to the difficulty in terms of accessibility to interact with the user interface. This differentiation underlines the importance of user-centered design and emphasizes the need to develop health monitoring systems that meet the different needs of all user groups.

Table 4 shows the average scores given by both staff and beneficiaries for the items in the UEQ-S, while Table 5 presents the scores given by the two groups in terms of PQ and HQ. For each dimension (PQ and HQ), the transformed scores were summed and then divided by the number of items in the respective category. The overall quality score was

calculated as the average of the PQ and HQ scores. The results of the UEQ-S questionnaire show that users highly appreciate both the PQ and HQ of the system. Among users, the system achieved a PQ score of 2.250 and an HQ score of 3.000, resulting in an overall quality score of 2.625. These results suggest that the system is not only highly functional but also emotionally appealing. The higher hedonic score indicates that the interface design and user experience resonate strongly with users and evoke a positive emotional response. While the pragmatic quality score is strong, its slightly lower value suggests opportunities for further improvement in task-related usability. For employees, the system received a PQ score of 2.000 and an HQ score of 2.250, resulting in an overall quality score of 2.125. These slightly lower scores, compared to those of beneficiaries, suggest that while staff find the system competent and effective, they may experience minor functionality or emotional engagement challenges. These differences between users and staff are probably due to the different contexts in which each group interacts with the system. Users may approach the system with lower initial expectations and find the interactivity with the system particularly appealing, increasing their hedonic perception. Usually, staff familiar with professional tools may prioritize pragmatic aspects such as efficiency and precision, resulting in slightly lower hedonic ratings.

TABLE IV. UEQ-S SCORES.

	Users	Staff	
Obstructive	2	1	**Supporting**
Complicated	2	3	**Easy**
Inefficient	2	1	**Efficient**
Confusing	3	3	**Clear**
Boring	3	2	**Exiting**
Not Interesting	3	2	**Interesting**
Conventional	3	3	**Inventive**
Usual	3	2	**Leading**

TABLE V. PRAGMATIC, HEDONIC, AND OVERALL QUALITY SCORES.

	PQ	HQ	Overall
Users	2.250	3.000	2.625
Staff	2.000	2.250	2.125

This balance between functionality and pleasure is critical for health monitoring applications, as it promotes both short-term effectiveness and long-term adherence. However, the UEQ-S overall scores of 2.125 for the staff and 2.625 for the elderly users highlight the system's strong ability to effectively support user tasks while providing engaging and positive user experience.

The SUS and UEQ-S questionnaires highlight different but complementary aspects of the system's performance. The SUS focuses on usability, emphasizing functionality, efficiency, and ease of learning, making it ideal to assess the effectiveness of the system in completing tasks. This explains the higher SUS scores from staff, prioritizing seamless integration into professional workflows. In contrast, the UEQ-S evaluates both usability and overall user experience, capturing emotional engagement and aesthetic appeal through its Pragmatic and Hedonic Quality dimensions. Together, these tools provide a holistic view, combining functional reliability with user-centered design insights.

The findings indicate the reliability and effectiveness of the rPPG system, especially among professional personnel. However, to achieve a universally excellent user experience, it is essential to address the specific challenges faced by elderly users. Refinements such as larger fonts, high-contrast color schemes, and a more guided user experience could significantly enhance accessibility and satisfaction, encouraging broader adoption in diverse settings. Moreover, this study focuses on short-term usability assessment. While initial feedback is positive, long-term user engagement and system sustainability are crucial aspects of health monitoring applications, warranting further investigation. While the sample size (N=27) is appropriate for an initial usability study, future research should involve a larger and more diverse participant pool to improve generalizability. Additionally, participants had different levels of prior exposure to digital health technologies, which could influence their perceptions of usability. Usability evaluations are inherently subjective and may be influenced by participants' prior experience with technology. Staff members, being more technologically proficient, reported higher usability scores, while elderly users encountered minor difficulties. Future studies should account for this factor by stratifying participants based on their digital literacy levels. The system interface was initially developed in Italian to match the target population. An English version was created for dissemination purposes, but future research should explore how cultural and linguistic factors may affect usability in international contexts. The study was conducted in two elderly care facilities, where participants had access to structured assistance. These results may not be fully generalized for older adults living independently or in different cultural and socio-economic contexts. Future research should expand the evaluation to diverse settings.

IV. CONCLUSION

This study investigated the usability of an rPPG-based system for non-invasive vital sign monitoring, particularly for elderly users. A total of 27 participants (20 care facility residents and 7 staff members) evaluated the system through SUS and UEQ-S. Staff rated it highly (SUS: 97.5), reflecting professional suitability, while beneficiaries gave it a strong but lower score (SUS: 80.0), indicating room for improved accessibility. Similarly, the UEQ-S results highlighted a positive balance between functionality and emotional engagement, with overall scores of 2.125 for Pragmatic Quality and 2.625 for Hedonic Quality. While previous methods have focused primarily on accuracy, our approach

emphasizes both technical performance and usability, making it a viable solution for real-world healthcare applications. These results underline the system's potential and highlight the necessity to improve it, ensuring wider acceptability and better user experience across different target groups. Future studies should explore long-term usability and effectiveness in diverse real-world scenarios, particularly focusing on iterative improvements based on user feedback from different demographic groups.

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REFERENCES

[1] N. Mohammadzadeh, M. Gholamzadeh, S. Saeedi, and S. Rezayi, "The application of wearable smart sensors for monitoring the vital signs of patients in epidemics: a systematic literature review," J Ambient Intell Humaniz Comput. vol. 14, no. 5, pp. 6027-6041, 2023.

[2] P. V. Rouast, M.T.P. Adam, R. Chiong, D. Cornforth, and E. Lux, "Remote heart rate measurement using low-cost RGB face video: a technical literature review," Front. Comput. Sci. Front. Comput. Sci. vol. 12, pp. 858-872, 2018.

[3] W. Verkruysse, L.O. Svaasand, and J. S. Nelson, "Remote plethysmographic imaging using ambient light," Opt Express. vol. 16, no. 26, pp. 21434-21445, 2008.

[4] R. J. Lee, S. Sivakumar, and K. H. Lim, "Review on remote heart rate measurements using photoplethysmography," Multimedia Tools and Applications, vol. 83, pp. 44699–44728, 2024.

[5] E. Takano et al., "User Experience of Older People While Using Digital Health Technologies: A Systematic Review," Appl. Sci. vol. 13, pp. 12815, 2023.

[6] A. Caroppo, A. Manni, G. Rescio, P. A. Siciliano and A. Leone, "Vital signs estimation in elderly using camera-based photoplethysmography," Multimedia Tools and Applications, vol. 83, pp. 65363–65386, 2024.

[7] J. Nielsen, Usability Engineering. Morgan Kaufmann Publishers, 1993.

[8] I. Maramba, A. Chatterjee, and C. Newman, "Methods of usability testing in the development of eHealth applications: a scoping review," International journal of medical informatics, vol. 126, pp. 95-104, 2019.

[9] International Organization for Standardization, ISO 9241-11:2018 Ergonomics of Human-System Interaction – Part 11: Usability: Definitions and Concepts, 2018.

[10] J. Lewis, B. Utesch, and D. Maher, "Measuring perceived usability: The SUS, UMUX-LITE, and AltUsability," Int. J. Hum.-Comput. Interact., vol. 31, no. 8, pp. 496-505, 2015.

[11] J. Brooke, "SUS: A quick and dirty usability scale," Usability Evaluation in Industry, vol. 189, no. 194, pp. 4–7, 1996.

[12] M. Schrepp, A. Hinderks, and J. Thomaschewski, "Design and evaluation of a short version of the User Experience Questionnaire (UEQ-S)," Int. J. Interact. Multimedia Artif. Intell., vol. 4, pp. 103-108, 2017.

Commercial Wrist Devices for Epileptic Seizure Detection: A Systematic Review

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***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]))

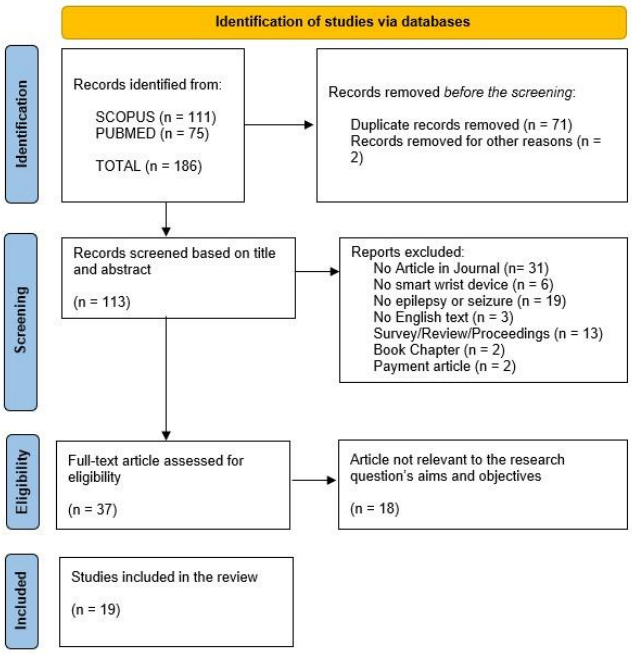

Figure 1. Flow diagram generated with PRISMA methodology, depicting the reviewers' process of finding published data on the considered topic and how they decided whether to include it in the review.

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.

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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.