Haipeng Liu · Gary Tse · Xinhong Wang ·
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Advanced Wearable Sensing in Clinical Practice Towards Healthcare 5.0

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Foreword

Imagine a world where your watch doesn't just tell time but silently listens to your heartbeat, tracks your breathing, and even warns you before illness onsets. A world where your shirt can sense exhaustion, your glasses understand your brain activity, and a tattoo-like patch on your skin replaces a complete diagnostic laboratory. This is no longer the territory of science fiction—it is the pulsation of the present day, beating ever quicker toward the future.

The chapters in this book form a tapestry woven with technology, life sciences, and imagination. Here, data science meets wearable devices; blockchain protects personal health information; flexible liquid metals bend to new possibilities; and advanced photodetectors open the eyes of the sensors to monitor our health. Each contribution challenges conventional technologies, push the limitations, and asks a simple but transformative question: Could the forthcoming of healthcare move with us, wherever we go?

Yet, wearable technologies are not only about sensors and electronics. They stand as pillars of **Healthcare 5.0**—an idea where healthcare advances into a tailored, prognostic, and hands-on ecosystem. Healthcare 5.0 blends artificial intelligence, Internet of things, cloud computing, blockchain, and human-centric design to enable individuals, diminish hospital burdens, and transform the very nature of medical care. The innovations described in these chapters embody this spirit: they move beyond treatment into prevention, beyond monitoring into empowerment, and beyond devices into ecosystems.

This book also highlights the true spirit of modern science: the **multidisciplinary approach**. Engineers, clinicians, data scientists, material scientists, and epidemiologists congregate here, reflecting how innovations today rarely appear from a single discipline. Instead, they are born at junctures—where signal processing meets cardiology, where material science meets biomedical engineering, where big data encounter artificial intelligence. It is a book not only for engineers and clinicians but for anyone curious about how the fabric of our daily lives is being rewoven into something smarter, more responsive, and more humane.

Wearable technology is no longer an accessory. It is an extension of the body, a mirror of the mind, and, increasingly, a protector of life itself. This book, with its outlooks and depth of insights, serves as both a roadmap and an invitation: to explore, to question, and to create the future we are already beginning to wear.

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Preface

The rapid advancement of **wearable sensing technologies** has fundamentally reshaped how health data are collected, analyzed, and utilized. From biocompatible, miniaturized sensors to intelligent devices and IoT-enabled platforms, wearables now offer **continuous, non-invasive, and multimodal monitoring** of physiological parameters that were once confined to clinical settings. These innovations form a cornerstone of **Healthcare 5.0**, a new era that emphasizes connectivity, intelligence, personalization, and preventive care towards precise medicine.

This book, *Advanced Wearable Sensing in Clinical Practice Towards Healthcare 5.0*, was conceived to **bridge the gap between technological development and clinical application**. While significant progress has been made in sensor design, data processing, and wireless communication, translating these advancements into real-world healthcare requires an integrated understanding of engineering principles, clinical contexts, and regulatory landscapes. Our goal is to provide such an integrated perspective.

The book is organized into fourteen chapters, each addressing a **key facet of wearable sensing**. The early chapters focus on foundational technologies—data analysis methods, signal processing techniques for wearable ECG bio-amplifiers, and blockchain for secure medical data handling. These sections provide essential technical grounding for understanding how wearable systems collect, process, and transmit data, and how they can be trusted in sensitive clinical environments.

Subsequent chapters explore **emerging techniques and sensing modalities**, such as gallium-based liquid metals and advanced photodetectors, which are enabling new levels of device flexibility, sensitivity, and integration. Applications in specific clinical domains are then examined, including **accelerometry in pediatric populations**, **automated arrhythmia detection**, **respiratory disease monitoring**, and **sleep tracking using low-cost wearable sensors**. By focusing on both the technical innovations and their clinical relevance, these chapters highlight the **translational potential** of wearable sensing technologies.

The later chapters address **system-level integration and future directions**, including deep learning frameworks for pulmonary disease detection, continuous in-hospital monitoring, chronic disease management, radio frequency sensing for daily activity tracking, and electrical impedance tomography for non-invasive screening. These topics exemplify how wearable technologies are moving from isolated tools to integral components of intelligent healthcare ecosystems.

This book is the result of joint contributions from a diverse group of researchers and clinicians around the world. Their collective expertise reflects the **interdisciplinary nature of wearable sensing research**, and their insights are aimed at readers who wish to understand not only where the field stands today but also where it is headed.

We hope this volume serves as a **comprehensive reference and an inspiration**—whether you are a researcher developing next-generation sensors, a clinician integrating wearable devices into patient care, or a policymaker shaping the future of digital health.

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Contents

Chapter 1
Advanced Data Analysis Methods for Wearable Device Data

Wenxin Xu, Wei Zhang, Tong Chen, Collin Sakal, Xiangrui Yao, and Xinyue Li

Abstract Modern wearable devices can provide continuous, high-resolution monitoring of physiological signals such as physical activity, sleep, and glucose levels, enabling clinicians and researchers to move beyond traditional survey data collection towards dynamic real-time health insights. Wearable sensing data has great potential to enhance clinical decision-making, facilitate early interventions, and support individualized care, while there are unmet challenges in processing real-time multimodal data. This chapter provides an overview of methodological advances in wearable sensing data analysis. Multimodal data fusion, functional data analysis, and predictive modeling have provided great potential for reliable processing on continuous monitoring data, and extracting clinical features. Empowered by artificial intelligence, the advanced data analysis techniques play a key role in expanding the application scenarios of wearable sensors, and transforming healthcare systems towards personalization, prevention, and data-driven decision making.

1.1 Introduction

As healthcare systems evolve towards emphasizing personalization, prevention, and intelligent integration, wearable sensing technologies have emerged as a cornerstone of this transformation. Modern wearable devices can provide continuous, high-resolution monitoring of physiological signals such as physical activity, sleep, and glucose levels, enabling clinicians and researchers to move beyond traditional survey data collection towards dynamic real-time health insights. Wearable device data has great potential to enhance clinical decision-making, facilitate early interventions, and support individualized care, but data analysis still remains challenging. Traditional approaches that rely on aggregated summaries often fail to capture the intricate

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temporal patterns inherent in sensor data, motivating the adoption of more advanced statistical tools.

Functional data analysis has emerged as a powerful framework to address these challenges by treating time series observations as continuous functions rather than isolated measurements. Through tools such as functional principal component analysis and scalar-on-function regression, functional data analysis facilitates dimension reduction, pattern recognition, and robust modeling of associations between functional predictors and health outcomes.

The integration of multi-modal wearable data spanning accelerometry, heart rate, temperature, and glucose levels in health studies has necessitated the development of advanced data fusion strategies. These include early, intermediate, and late fusion approaches, each tailored to harmonize disparate data types for downstream machine learning or statistical modeling. Such integration enables a more holistic understanding of health behaviors and outcomes, particularly when combined with interpretable models and visualization techniques.

Wearable devices possess transformative potential in public health surveillance and personal health monitoring. Applications of advanced methods have already begun to reshape our understanding of sleep, physical activity, and chronic disease management. From predicting sleep efficiency using physical activity profiles to modeling glucose variability with functional data analysis, wearable device data enable new frontiers in population health, epidemiology, and individualized health management.

This chapter provides an overview of methodological advances in wearable device data analysis. It outlines foundational methodologies, integration frameworks, and real-world applications that are collectively driving the next generation of intelligent, data-driven clinical practice.

1.2 Multi-Modal Data Integration Analysis

The advent of wearable sensing technology has revolutionized healthcare by enabling continuous, non-invasive monitoring of physiological parameters. These devices generate a plethora of data types, capturing various aspects of an individual's health status. However, the true potential of wearable devices in clinical practice is realized when data from multiple modalities are integrated and analyzed holistically. Multi-modal data integration combines diverse data sources, such as physiological signals, activity patterns, and environmental factors, to provide a comprehensive view of patient health. Integrating multi-modal data addresses the complexity inherent in health monitoring, where single data streams may not capture the full picture. This integration enhances diagnostic accuracy, enables personalized interventions, and improves patient outcomes. This section explores the strategies and methods for multi-modal data integration, discusses the analytical techniques employed, and highlights applications in clinical practice.

1.2.1 Fusion Strategies in Multi-Modal Data Integration

Effective integration of multi-modal data is crucial for leveraging complementary information across different sources. Fusion can occur at various stages of the data analysis pipeline: data-level (early fusion), feature-level (intermediate fusion), and decision-level (late fusion). Each strategy presents unique advantages and trade-offs, and the optimal choice depends on the application scenario and the characteristics of the data involved.

Data-Level Fusion (Early Fusion)

Data-level fusion combines raw signals from multiple modalities into a unified input prior to feature extraction. This approach preserves the original information and temporal alignment between streams. Key components include:

1. Synchronization: Aligning data streams in time, particularly when sampling rates vary, using techniques such as interpolation and resampling [1].
2. Preprocessing: Applying noise reduction, filtering, and normalization to ensure cross-modal compatibility.
3. Concatenation: Merging preprocessed data arrays into a composite input for downstream analysis.

Data-level fusion preserves the richness and detail of raw data and captures interactions between modalities at the signal level. However, its high dimensionality increases computational complexity, and data heterogeneity may introduce noise and redundant information.

Feature-Level Fusion (Intermediate Fusion)

Feature-level fusion involves independently extracting features from each modality and then aggregating them into a joint representation. This strategy allows for modality-specific preprocessing while enabling joint modeling:

1. Feature extraction: Domain-specific techniques are used to derive meaningful descriptors (e.g., statistical metrics, frequency-domain features).
2. Dimensionality reduction: Methods such as Principal Component Analysis reduce feature dimensionality [2] to avoid redundancy and overfitting.
3. Feature combination: Fusion methods include concatenation, averaging, or learned weighting schemes.

Feature-level fusion reduces data size compared to raw data fusion and allows for modality-specific feature extraction methods. However, it might result in the potential loss of temporal information and require careful feature selection to avoid irrelevant or redundant features.

Decision-Level Fusion (Late Fusion)

Decision-level fusion combines the outputs or decisions from multiple models, each trained on different modalities, to produce a final decision:

1. Voting schemes: Techniques such as majority voting or weighted voting based on model confidence.
2. Bayesian methods: Probabilistic frameworks that account for uncertainty in decision-making [3].
3. Ensemble methods: Techniques such as stacking or boosting to aggregate decisions and enhance predictive performance.

Decision-level fusion is flexible, allowing the use of different models tailored to each modality, and is robust to the failure of individual modalities. However, it requires effective strategies to resolve conflicting decisions and may overlook correlated information between modalities.

1.2.2 Integration Analysis Methods

Analyzing integrated multi-modal data requires robust methods capable of capturing complex interdependencies and extracting meaningful patterns.

Machine Learning Approaches

Machine learning models, particularly deep learning architectures, can process multi-modal inputs to perform tasks such as classification, regression, or prediction.

1. Supervised learning
   - Convolutional Neural Networks (CNNs): Effective for spatially structured data, adaptable to physiological signals [4].
   - Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) Networks: Handle sequential and temporal data effectively [5].
   - Multi-input models: Architectures that accept simultaneous inputs from different modalities [6].
2. Unsupervised learning
   - Clustering: Methods such as K-means or hierarchical clustering group data based on similarity.
   - Anomaly detection: Methods that can identify outliers or unusual patterns in integrated representations.

Statistical Methods

Statistical approaches offer interpretable insights into multi-modal relationships:

1. Multivariate analysis
   - Canonical Correlation Analysis (CCA): Explores relationships between two sets of variables from different modalities [7].
   - MANOVA (Multivariate Analysis of Variance): Assesses differences across groups considering multiple dependent variables.
2. Probabilistic models:
   - Bayesian networks: Model probabilistic dependencies and uncertainties among variables.
3. Dimensionality Reduction:
   - Principal Component Analysis (PCA): Reduces data complexity while preserving variability.
   - t-Distributed Stochastic Neighbor Embedding (t-SNE): Visualizes high-dimensional data in lower-dimensional space for pattern discovery [8].

Integration analysis faces several challenges, including data heterogeneity, temporal alignment, missing data, and computational complexity. Data heterogeneity arises because different modalities produce data in varying formats, scales, and distributions, requiring standardization techniques and the adoption of interoperability standards to bring data onto a common scale and facilitate integration. Temporal alignment and synchronization are essential when dealing with sequences of differing lengths or speeds. Missing data is another significant issue, addressed through imputation methods such as mean imputation or more sophisticated techniques such as K-Nearest Neighbors (KNN) imputation to estimate missing values. Lastly, computational complexity presents challenges in scalability and efficiency, which can be mitigated by implementing efficient algorithms, leveraging high-performance computing resources, and reducing algorithmic complexity through optimization and approximation methods.

1.2.3 Applications

1. Data and feature-level fusion for wellbeing prediction: Li et al. [9] investigated the effectiveness of early fusion versus late fusion strategies in multimodal data integration for predicting subjective wellbeing measures such as mood, health, and stress. They used data from skin conductance, skin temperature, and acceleration sensors. In the early fusion approach, raw data from all three modalities were concatenated and processed jointly through a denoising autoencoder,

enabling the model to learn shared representations that capture cross-modal interactions from the outset. In contrast, the late fusion strategy involved independent feature extraction from each modality via autoencoders, followed by feature-level combination. The results showed that early fusion consistently outperformed late fusion, exhibiting lower reconstruction loss during representation learning and improved prediction accuracy on unseen participants. The authors suggested that early fusion was more effective for personalized tasks because it better captured critical features and produced smoother, more coherent representations.

2. Feature-level fusion via graph-attention networks: Wang et al. [10] proposed an attention-based method for predicting affect status by analyzing multivariate time series data collected from multiple wearable devices, including the OURA ring, Samsung smartwatch, and smartphone. The approach integrates physiological, behavioral, and contextual modalities to provide a comprehensive understanding of affective states. Their fusion methodology combines self-attention mechanisms with Graph-Attention Layers (GAT) to capture both temporal dependencies and relationships between different modalities. Specifically, each modality is first processed independently through a self-attention mechanism to capture temporal patterns. Then, a GAT layer is employed where each node represents an embedded value from a specific modality, and edges signify dependencies between modalities. This dual-level integration allows the model to offer interpretability at both temporal and modality levels. Their model achieved an accuracy of 78.62% for predicting positive effects and 76.30% for negative effects. The results demonstrated that interactions related to physical activity were most predictive for positive effects, while sleep and heart rate variability modalities were most predictive for negative effects. This study exemplifies how multimodal feature-level fusion can enhance both predictive performance and interpretability in wearable health monitoring applications.
3. Hierarchical feature fusion in gesture recognition: Yuan et al. [11] developed a hand gesture recognition system using a novel data glove that integrates multiple sensor modalities, three-dimensional flex sensors, gyroscopes, and accelerometers, to capture fine-grained hand movements. Their fusion strategy centers on a Deep Feature Fusion Network (DFFN) designed to integrate both low-level (shallow features retaining fine spatial resolution) and high-level (deep semantic features capturing abstract motion patterns) features from different sensors. These features are extracted using convolutional layers and concatenated at the feature level to leverage the strengths of both feature types. To model the temporal dependencies inherent in complex gestures, the fused features are processed through a LSTM network. This two-stage integration, feature-level fusion across modalities followed by temporal modeling, enables the system to accurately interpret detailed finger movements and broader arm gestures. Evaluated on datasets for American Sign Language and Chinese Sign Language, the system achieved accuracies of 99.93% and 96.1%, respectively, outperforming models that used unimodal or non-integrated features. This work demonstrates the effectiveness of hierarchical multimodal feature-level fusion in wearable systems for precise and naturalistic gesture recognition.

4. Decision-level fusion for activity monitoring: Lin et al. [12] introduced an Adaptive Multi-Modal Fusion Method (AMFM) for monitoring daily activities in individuals with mobility disabilities by integrating visual and inertial data. Their framework processes video data using an Attention-based Spatio-Temporal Graph Convolutional Network (ALSTGCN) and inertial data using a Long Short-Term Memory Fully Convolutional Network (LSTM-FCN). The core of their integration approach is a decision-level fusion with an adaptive weight learning strategy, enabling the model to dynamically adjust the contribution of each modality based on the specific activity being classified. This adaptive weighting ensures that the most informative modality is emphasized for each task, for example, relying more on inertial data for detecting subtle limb motions or on visual data for complex posture changes. Evaluated on three datasets, including their own H-MHAD dataset designed for heterogeneous motion capture, their method achieved 91.8% accuracy in general activity recognition and 100% recall in fall detection. This study demonstrates the effectiveness of adaptive, modality-aware decision-level fusion strategies in enhancing the robustness and clinical utility of wearable systems for mobility assessment.

1.3 Functional Data Analysis for Wearable Signals

Wearable devices can continuously monitor signals including accelerations, heart rates, body temperature, etc. With the development of manufacturing, wearable devices collect signals with high resolution. For instance, Actigraph GT3X can provide acceleration data measured at minute-level or even Hz-level, which enables the characterization of specific physical activity patterns. Therefore, advanced wearable devices allow for a rich collection of data, while the extraction of useful information from multivariate signals remains a challenge. Traditional research on wearable device data has typically relied on summarized metrics, such as accumulated day-level activity counts and total daily time spent engaging in moderate or vigorous physical activity. Although these summaries offer useful insights, they inherently disregard the temporal dynamics and correlations across time points, leading to considerable information loss. Given the densely and regularly sampled nature of wearable signals that often exhibit complex temporal and spatial structures, functional data analysis provides an effective framework for capturing and modeling the latent information embedded in these high-frequency data streams.

1.3.1 Introduction

Functional Data Analysis (FDA) provides a powerful framework for analyzing functions. The functional data are high-dimensional data sampled over a specified domain. For example, accelerometer data are sampled over the day for each individual. Instead of treating the observations independently, FDA considers the observations as a whole, analyzes the trends and correlations over the functional domain, and relates the functions with scalar covariates.

In FDA, observed functions are denoted by $W_i(s): S \to \mathbb{R}$, where S is the functional domain, and i is the index of study participants. We always assume that $W_i(s) = \mu(s) + X_i(s) + \epsilon_i(s)$, where $\mu(s)$ is the functional mean, $X_i(s) : S \to \mathbb{R}$ is the true functional process and $\epsilon_i(s)$ is the independent random error with distribution $N(0, \sigma^2)$ occurred at each observation point within the function. The mean $\mu(s)$ is assumed to be a fixed function and $X_i(s)$ is a random process with distribution $N(0, \Sigma_i(s, s'))$, where $\Sigma_i(s, s') = cov(X_i(s), X_i(s'))$ is the covariance function between $X_i(s)$ and $X_i(s')$. Both $\mu(s)$ and $X_i(s)$ are expected to be smooth along domain S. Though we expect the functions to be continuous on the domain, in the real-world scenario, we can only sample the functions in discrete time points and raise the resolution of the sampling grids to achieve 'smoothness'.

1.3.2 Methodological Foundations

We now introduce the theoretical foundations for FDA that are commonly used for wearable device data analysis.

Functional Principal Component Analysis

Consider the case where we collect data from n participants, each with p observations, then the data matrix is of dimension $n \times p$. In general, p is huge due to the dense sampling scheme of wearable devices, which leads to severe computation burdens in the case of direct multivariate regression. However, when we treat these observations as functional data, dimension reduction techniques such as functional principal component analysis (FPCA) can be used. For the random process $X_i(s) \sim N(0, \Sigma_i(s, s'))$, by Mercer's theorem, $\Sigma_i(s, s') = \sum_k \lambda_k \phi_k(s)\phi_k(s')$, where $\lambda_1 \geq \lambda_2 \geq \cdots \geq 0$ are the ordered eigenvalues and $\phi_k(s)$ are the orthogonal eigenfunctions of the covariance function. Then $W_i(s)$ can be expressed by the Karhunen–Loève (KL) expansion $W_i(s) = \mu(s) + \sum_k \xi_{ik}\phi_k(s) + \epsilon_i(s)$, where ξ_{ik} are the eigenscores with mean 0 and variance λ_k. $\xi_{ik} = \int X_i(s)\phi_k(s)ds$ can be calculated by numerical integration or estimated directly through Best Linear Unbiased Predictor (BLUP).

Multilevel Functional Principal Component Analysis

The FPCA method is efficient in dimension reduction and captures the principal variation direction of data. However, it is not designed for datasets with complex hierarchical sampling structures, for instance, in most accelerometer surveys, participants were asked to wear the accelerometer for a consecutive week or multiple times, in which the subject-level curves are repeatedly collected. In these cases, one-level FPCA may ignore the variation in the activity patterns across different visits. Di et al. [13] developed a two-level FPCA which has the following form:

$$W_{ij}(s) = \mu(s) + U_i(s) + V_{ij}(s) + \epsilon_{ij}(s), \tag{1.1}$$

where $U_i(s)$ is the subject level random process, $V_{ij}(s)$ is the visit level random process, i represents the index of subjects, and j represents the index of different visits. The covariance functions are $K_U(s,t) = cov(U_i(s), U_i(t))$ and $K_V(s,t) = cov(V_{ij}(s), V_{ij}(t))$, respectively. Greven et al. [14] generalized the work to longitudinal FPCA (LFPCA) by adding a random slope into the subject-level random process:

$$W_{ij}(s) = \mu(s) + B_{i0}(s) + B_{i1}(s)T_{ij} + V_{ij}(s) + \epsilon_{ij}(s). \tag{1.2}$$

Under the dense and regular sampling design, Staicu et al. [15] generalized the functional predictors to a two-dimensional setting to account for the complex variation along the longitudinal direction as well as recover the true functional trajectories. The decomposition of the functional predictor becomes

$$W_i(s,t) = \mu(s,t) + X_i(s,t) + \epsilon_{ij}(s), \tag{1.3}$$

The Karhunen–Loève (KL) expansion of two-dimensional random process is decomposed into functional direction and longitudinal direction separately and has the form $X_i(s,t) = \sum_{k\geq 1}\xi_{ik}(t)\phi_k(s)$, where $\xi_{ik}(t)$ are zero-mean smooth processes along the longitudinal direction. Lin et al. [16] constructed a three-level FPCA and decomposed the functional predictor effects into subject-, visit-, and day-level, and the estimation was made through a combination of least-squares regression and the method of moments estimator (MoM). To facilitate the computation of multilevel FPCA (MFPCA), Cui et al. [17] proposed a fast MFPCA procedure based on the fast covariance estimation (FACE) method developed by Xiao et al. [18]. The FACE method accelerated the eigen-decomposition procedure by adding a sandwich smoother to smooth the covariance function estimator. Cui et al. employed the FACE to conduct eigen-analysis on both the subject-level and visit-level covariance functions, and then estimate the corresponding functional principal component scores through mixed model equations.

Multilevel Scalar-On-Function Regression

FDA allows us to find the associations between health attributes or mortality risks with functional predictors. Similar to the linear regression approach, in FDA, existing work uses scalar-on-function regression (SoFR) to deal with Gaussian or non-Gaussian scalar-outcomes [13, 15, 16, 19–21]. The basic representation of a multilevel SoFR model is as follows:

$$E[Y_{ij}] = \alpha + b_i + \int U_i\big(s, T_{ij}\big)\beta_U(s)ds + \int V_{ij}(s)\beta_V(s)ds \tag{1.4}$$

where b_i is the subject specific random effect and follows the distribution $b_i \sim N(0, \sigma^2)$, and $U_i\big(s, T_{ij}\big) = U_{i0}(s) + U_{i1}(s)T_{ij}$ for the LFPCA and $U_i\big(s, T_{ij}\big) = U_i(s)$ for the MFPCA. The estimation approach for Eq. (1.3) was first systematically specified by Goldsmith et al. [20] through functional principal component regression (FPCR) and penalized functional regression (PFR). The difference between these two methods lies in the assumptions of the bases of functional predictors. The FPCR method expands both functional predictors and coefficients using the eigenfunctions of the covariance functions $K_U(s, t)$ and $K_V(s, t)$, while the PFR method uses the spline bases to construct functional coefficients. The advantage of the latter is that the complex Eq. (1.3) can be flexibly estimated using well-constructed, standard mixed effects models. Furthermore, the functional coefficients of PFR were constructed using a combination of 'completely smooth' bases and 'wiggliness' random effects, which benefits the model inference on whether a simpler model would be a better fit than the complex model. The assumption of two dimensional functional coefficients were considered by Kundu [19] and Staicu et al. [15]. These more complex model designs adopted both FPCR and PFR to decompose the functional coefficients as well as functional predictors, and the estimation relies on converting functional regression models to linear mixed effect models or generalized additive mixed models.

1.3.3 Application

1. Physical activity (PA) patterns monitoring and health care biomarkers regression via multilevel SoFR model. Xu et al. [22] performed MFPCA to capture the principal physical activity patterns by the leading subject-level eigen-components. Health outcomes such as insulin, C-reactive protein (CRP), and quality of life were found to be strongly associated with PA volume and temporal patterns through an MFPCA score regression. The results suggested that high volume PA will significantly improve insulin resistance, CRP level, and physical and mental health of the cohort of participants.
2. Repeatedly collected obesity-related health outcomes regression via the longitudinal SoFR model. Lin et al. [23] extended the work of [22] by incorporating both subject- and visit-level FPCA scores obtained from LFPCA decomposition as predictors in the SoFR model. Both level 1 and level 2 leading scores are negatively associated with health outcomes such as insulin, CRP, and BMI, demonstrating that increased PA between visits has a significant impact on the decline in these health biomarkers. Lin et al. [16] further generalized the LFPCA model to a multilevel longitudinal functional principal component model to account

for the variation induced by hierarchical sampling schemes. The model captured more detailed PA patterns and suggested that an earlier PA engagement on one day benefits in the mitigation of obesity risks.

3. Multivariate SoFR in physical health assessments. Cao et al. [24] proposed a functional adaptive double-sparsity (FadDos) estimator for a multivariate functional SoFR model. The model was designed to analyze the relationship between the Balance Evaluation Systems Test (BESTest) score, a metric for physical health ability, and the Kinect Sensor functional data. The FadDos estimator achieves both global- and local-sparsity and enables variable selection of multiple functional predictors as well as the interpretability of the corresponding functional coefficients. In addition, the estimator is theoretically stable and enjoys oracle properties. The results exhibit clustering effects of behavior related to major skeleton joints in the head, limbs, trunk, etc., and suggest that a series of movement features when standing up, walking, and sitting are strongly related to the mobility assessment scores.
4. Function-on-scalar regression (FoSR) on dynamic PA monitoring. Cao et al. [25] constructed a two-dimensional functional mixed effect model (2DFMM) framework to account for the intraday and interday interactions between PA patterns and students' information, such as demographic and socioeconomic status, physical and mental health characteristics. The 2DFMM concentrated on densely and repeatedly measured functional responses and developed the corresponding estimation and inference methods based on the marginal covariance decomposition techniques. The model generates two-dimensional functional coefficients within one week, and the results indicate that the PA level is strongly depressed by education schedule, study pressure, and education levels, especially during weekdays.

1.4 Wearable Data for Continuous Glucose Monitoring and Modeling

1.4.1 Introduction

Continuous glucose monitoring (CGM) systems have emerged as the gold standard for glycemic management, offering an effective approach to monitoring blood glucose levels in individuals with diabetes [26]. CGM systems generally comprise three main components: a sensor, a transmitter, and a receiver. These devices measure glucose concentrations in interstitial fluid, transmit the data to a receiver, and estimate blood glucose levels. This minimally invasive technology eliminates the need for traditional finger-prick tests or blood collection, significantly improving the convenience and comfort of glucose monitoring. Furthermore, CGM devices provide users and healthcare providers with a comprehensive view of glucose patterns and fluctuations over time, enabling a more holistic understanding of an individual's glycemic status and supporting more informed clinical decision-making. This section examines the challenges associated with CGM data analysis, explores advanced modeling methodologies, and highlights the applications of CGM data analysis, emphasizing their critical role in continuous data collection and personalized diabetes care.

1.4.2 Challenges in CGM Data Analysis

Data Characteristics and Preprocessing Challenges

Fundamental challenges stem from the way CGM data is collected (Fig. 1.1). Common CGM devices record glucose readings every 1–15 min, accumulating up to 1,440 data points per day for each individual. This continuous monitoring produces extensive datasets, necessitating efficient storage and management prior to analysis. Moreover, the time-series nature of CGM data demands scalable and robust analytical approaches to extract meaningful insights from this large volume of longitudinal data, thereby supporting clinical decision-making.

Although the accuracy of CGM devices has improved significantly over time, data quality issues remain a critical concern. During CGM data collection and

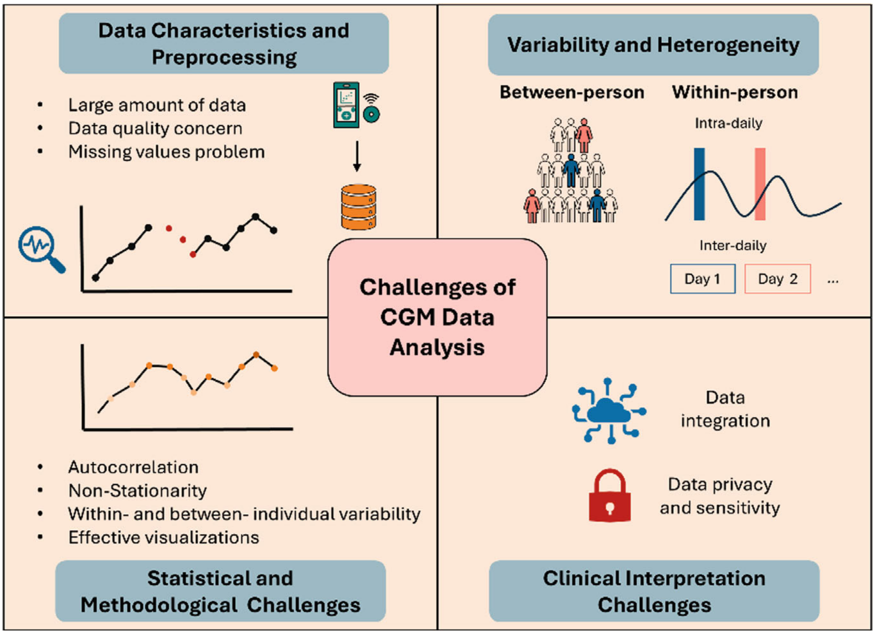

Fig. 1.1 Summary of challenges in CGM data analysis, categorized into data characteristics and preprocessing, variability and heterogeneity, statistical and methodological challenges, and clinical interpretation challenges

storage, measurement duplication and noise are often inevitably introduced [27, 28], creating complications for subsequent analysis, particularly when the data is collected under free-living conditions. These issues can obscure true glucose fluctuations and compromise the reliability of the data. To address these concerns, preprocessing pipelines that include noise filtering and robust statistical techniques are essential.

Additionally, technical issues such as sensor detachment, device malfunction, or insertion errors frequently disrupt CGM usage [29], leading to missing values. The wireless connectivity of CGM devices introduces further interruptions, as interruptions caused by Bluetooth or Wi-Fi disconnections can result in incomplete datasets. User-related factors, such as discomfort, skin irritation, and the burden of frequent sensor changes, can also affect adherence and contribute to data gaps or missingness. Therefore, accurate data imputation methods are crucial during the early stages of CGM data analysis to ensure the reliability and completeness of the datasets.

Variability and Heterogeneity Challenges

The analysis of CGM data is further complicated by the significant variability and heterogeneity observed in glucose patterns (Fig. 1.1), both between individuals and within the same individual over time [30]. While CGM devices are increasingly utilized for glucose monitoring in individuals with diabetes, inter-individual variability remains a hallmark of the condition. This variability arises from numerous factors, including differences in disease etiology, genetic predispositions, and individual responses to lifestyle modifications such as diet and exercise. This inherent heterogeneity poses challenges in developing generalized models or universal guidelines for CGM data analysis and interpretation.

In addition to inter-individual variability, substantial intra-individual variability further complicates CGM data analysis. Glucose levels can vary significantly within a single day (short-term variability) and across days (long-term variability) [31]. These fluctuations are influenced by a wide range of factors, including meal composition and timing, physical activity levels, sleep patterns, and hormonal changes. The high temporal variability in glucose levels makes it challenging to establish stable baseline patterns or to reliably predict future glucose excursions based on short-term observations.

Addressing these challenges requires long-term monitoring and the application of advanced time-series analysis techniques capable of capturing dynamic fluctuations. Such methods must also distinguish between normal physiological variations and clinically significant events, ensuring accurate assessment and interpretation of CGM data.

Statistical and Methodological Challenges

Given its continuous and longitudinal nature, CGM data inherently presents several statistical and methodological challenges (Fig. 1.1). One key issue is the presence of autocorrelation, where consecutive glucose readings are not statistically independent. Additionally, long-term trends or changes in an individual's health status can lead to non-stationarity in the data, meaning that its statistical properties change over time. Traditional statistical methods that assume independence of observations may yield inaccurate results when applied to CGM data. In addition, as previously mentioned, variability exists both within and between individuals in CGM data. Therefore, specialized time-series analysis techniques that explicitly account for within-individual variability, autocorrelation, non-stationarity are preferred when analyzing CGM data. These complexities pose significant challenges in the accurate analysis and interpretation of CGM data.

Furthermore, simply presenting raw CGM data or summary statistics to patients and clinicians is often insufficient to drive meaningful changes in behavior or treatment regimens. Effective visualizations that clearly illustrate glucose trends and patterns are essential throughout the CGM data analysis process. These techniques can help interpret the data and suggest appropriate actions, such as detecting glucose changes related to meals or exercise, or identifying hazardous events like hypoglycemia. Visualizations play a crucial role in translating complex data into practical, actionable insights for both patients and healthcare providers. However, creating effective visualizations introduces additional challenges to the analysis of CGM data, requiring careful design and advanced analytical techniques to ensure clarity and utility.

Clinical Interpretation Challenge

The ultimate goal of CGM data analysis is to generate clinically actionable insights and enable timely decisions. However, this is hindered by challenges in integrating CGM data with other relevant datasets (Fig. 1.1). While CGM data provides a continuous measure of glucose levels, it does not offer insights into the factors driving glycemic fluctuations. Information such as meals, physical activity, sleep patterns, and stress levels are essential for accurate interpretation for glucose trends. Unfortunately, such contextual data is often incomplete or inconsistently recorded, especially when relying on self-reports, which makes it difficult for healthcare providers to obtain a holistic view of a patient's health status. A promising approach is to leverage wearable devices and mobile applications that can collect complementary data. For instance, physical activity data can be obtained from accelerometers, while heart rate variability can serve as a proxy for stress. Developing standardized frameworks for multimodal data fusion is also a challenging area of research.

In addition to the challenges of method development, the integration of sensitive health data from multiple sources raises significant concerns regarding data privacy, security, and ownership. Robust data governance frameworks, stringent security measures, and clear guidelines on data access and ownership are essential to ensure the responsible and ethical use of integrated CGM data while maintaining patient trust.

1.4.3 Modeling Approaches

With the increasing adoption of CGM devices in clinical and research settings, two major streams have emerged for analyzing the associations between CGM data and other health-related variables: approaches based on summary statistics and approaches leveraging functional data analysis techniques.

CGM-Derived Metrics Approaches

The Advanced Technologies & Treatments for Diabetes (ATTD) Congress convened an international group of clinicians and researchers in 2017 to establish standardized metrics for evaluating CGM data [32]. These metrics were subsequently adopted to simplify the analysis of CGM data. They include glycemic in-range indicators such as Time in Range (TIR), Time Above Range (TAR), and Time Below Range (TBR), typically based on a common target range of 70–180 mg/dL (3.9–10.0 mmol/L). To further capture the temporal dynamics of CGM data, measures of glycemic variability were also recommended, including the Coefficient of Variation (CV) and Standard Deviation (SD). Although not formally introduced during the congress, additional variability metrics such as Mean Amplitude of Glycemic Excursions (MAGE) and Mean of Daily Differences (MODD) have been proposed, each offering a different perspective on how glucose variability is quantified.

In addition, a standardized format for CGM data visualization called the Ambulatory Glucose Profile (AGP) has been proposed by a consensus [33]. These metrics include days of CGM wear, mean glucose, estimated HbA1c based on the CGM data, glucose variability (% CV or SD), two measures of time above range >250 mg/dL (13.9 mmol/L) and >180 mg/dL (10.0 mmol/L), time in range 70–180 mg/dL (3.9–10.0 mmol/L), and two measures of time below range or hypoglycemia <70 mg/dL (3.9 mmol/L) and <54 mg/dL (3.0 mmol/L).

These metrics provide a simplified yet informative summary of glycemic control and variability. In modeling, these summary metrics are commonly used as predictors or outcomes in correlation analyses, linear or logistic regression models, and survival analyses. Such approaches are particularly useful for examining relationships between CGM-derived metrics and various clinical or behavioral factors. The advantage of these metrics lies in their interpretability and direct relevance to clinical practice, as they allow for straightforward communication between healthcare providers and patients. However, by reducing CGM data to a small set of aggregate measures, important temporal dynamics and detailed patterns within glucose trajectories may be overlooked, which could limit the granularity of the insights derived from the data.

Functional Data Analysis-Based Approaches

To preserve and leverage the full temporal complexity of CGM measurements, Functional Data Analysis (FDA) techniques have increasingly been adopted. In FDA, CGM data are treated as continuous functions over time rather than as discrete points. This perspective enables more sophisticated analyses that account for the entire glucose profile across one or multiple days. Although the application of FDA techniques remains understudied in the current literature (as reviewed later), the inherent nature of CGM data aligns well with the principles of FDA. Functional Analysis of Variance (FANOVA) can be applied to test significant differences in glucose dynamics across groups by comparing their mean functions over time. Functional Principal Component Analysis (FPCA) can be used to explore variability, identify key patterns in glucose dynamics, or clustering via glucose patterns. Functional regressions can be used to model associations between CGM data and diverse covariates. Specifically, Scalar-on-Function Regression (SoFR) models the relationship between functional predictors and scalar outcomes, while Function-on-Scalar Regression (FoSR) captures how scalar predictors influence entire functional responses. Function-on-Function Regression (FoFR) further extends this framework by modeling interactions between two function-valued variables over time.

1.4.4 Application

The application of CGM data analysis has demonstrated significant potential in advancing diabetes care and research, particularly through the use of CGM-derived metrics and FDA-based approaches. These techniques provide unique insights into glucose dynamics, supporting clinical decision-making and improving patient outcomes.

CGM-Derived Metrics Application

CGM-derived metrics have been widely used due to their simplicity and ease of integration into existing analytical frameworks. These models rely on standardized in-range metrics such as TIR, TAR, TBR and measures of glycemic variability, which provide concise and interpretable summaries of glycemic control. In previous review study, Kovatchev emphasized the importance of glycemic variability as a critical marker for evaluating glucose control, noting how the temporal fluctuations captured by CGM devices can complement traditional HbA1c measurements [34]. This study also highlighted key applications of CGM-derived metrics, including hypoglycemia prediction, the composition of artificial pancreas systems, and assessing the effectiveness of therapeutic agents.

Additionally, systematic reviews by Yapanis and colleagues have demonstrated that CGM-derived metrics, including both in-range metrics (e.g., TIR) and measures of variability (e.g., SD), are associated with a variety of diabetes-related complications, including microvascular and macrovascular conditions, nephropathy, retinopathy, and neuropathy [35]. Importantly, these associations have been shown to remain statistically significant even after adjusting for HbA1c, underscoring the value of CGM data in providing a more comprehensive assessment of glycemic control. These models are particularly useful for identifying patients at risk of complications, optimizing therapy, and evaluating the impact of lifestyle and pharmacological interventions. By offering actionable insights into glucose patterns, summary statistics-based models have become indispensable tools in clinical research.

Applications of Functional Data Analysis-Based Models

While summary statistics provide a simplified view of CGM data, FDA-based models enable a more detailed exploration of glucose dynamics by preserving the full temporal complexity of CGM measurements. However, there is limited research exploring the application of FDA to CGM data. Four previous studies applied FANOVA to gain a better understanding of CGM data and its association with the development of large-for-gestational-age outcomes among women with treated gestational diabetes [36–39]. Two other studies utilized FPCA to capture the main patterns of glycemic variation [40, 41], which were subsequently applied in prediction tasks or used to model nocturnal glucose levels.

Functional regression models have been employed in several studies, with CGM data serving as either functional predictors or functional responses. Matabuena and colleagues introduced nonparametric regression techniques to model glucose density functions derived from CGM devices, and later applied to characterize postprandial glucose dynamics [42, 43]. Xu and colleagues extended the application to 24-h CGM profiles and examined the temporal associations of time-restricted eating and diets with glucose levels [44]. Díaz-Rizzolo and colleagues explored the association between quinoa consumption and postprandial glycemic responses, while Sergazinov et al. analyzed nocturnal glucose patterns in a case study involving individuals with type 2 diabetes [45, 46].

By capturing the full temporal complexity of glucose data, these models offer a comprehensive understanding of individual glucose patterns, enabling clinicians to make more informed decisions and researchers to uncover novel insights into diabetes management.

1.5 Predictive Modeling and Association Studies in Public Health

1.5.1 Objectively Assessing Sleep and Physical Activity

Two tenets of a "healthy lifestyle," or living in such a way that reduces individual risk of adverse health outcomes, are sleep and physical activity. Advancements in wearable device hardware and machine learning have led to the development of algorithms that can leverage accelerometer data to detect sleep [47], step counts [48], and estimate physical activity intensity [49]. The use of wearables for sleep and activity tracking overcomes two central limitations of survey-based data collection: recall bias and limited information capture. Furthermore, modern wearables often have user interfaces that provide a platform for individualized interventions and allow users to interact with the data their device collects.

1.5.2 Applications in Epidemiological Research

Early wearable-based epidemiological studies sought to confirm whether prior survey-based sleep and physical activity findings held true when using objective measures. More recently, studies have begun leveraging the full potential of wearable device data to examine the relationships between more complex measures of sleep and physical activity with adverse health outcomes.

Using wearable device data from over 25,000 adults in the United Kingdom, Stamatakis et al. showed that vigorous intermittent physical activity, or short bursts of activity lasting less than 2 min, are associated with a reduced risk of mortality [50]. Their work was the first to confirm using objective measures that adults could potentially reduce their risk of adverse health outcomes by integrating small bouts of physical activity into their daily lives. Accelerometer data has also allowed for the quantification of novel activity phenotypes such as "Weekend Warriors," individuals who meet the World Health Organization's moderate-to-vigorous-activity recommendations of >150 min per week with 50% or more occurring over 1–2 days, were at a lower risk of dementia [51].

For sleep, wearables have enabled measures previously only quantifiable in sleep laboratories to be captured in population cohorts. Sleep efficiency represents the proportion of time spent asleep between initial sleep onset and final sleep offset and is impossible to accurately quantify using survey data. Wearable studies have found that high sleep efficiency is associated with better cognitive function [52] and a lower mortality risk [53]. Wearable studies have also led to the emergence of sleep regularity's recognition as an important health behavior, as some evidence has found sleep regularity to be more strongly associated with mortality than sleep duration [54].

1.5.3 Applications in Personal Health Monitoring

One of the earliest wearables widely used for personal health monitoring was the pedometer, or step counter, which was first popularized in Japan. In the years since, wearables such as smart watches have become capable of tracking sleep, physical activity, and providing estimates for other factors such as stress. While such measures have become popular among health and fitness enthusiasts, uncertainty remains regarding how wearables can be integrated into healthcare systems to enable out-of-clinic personal health monitoring. However, recent evidence is beginning to suggest several promising use-cases.

Cognitive function declines with age, but monitoring cognitive function is difficult due to the expertise needed to administer cognitive tests that lack test–retest reliability if administered too frequently. Several recent studies by Sakal et al. [55], Rykov et al. [56], and Butler et al. [57] have demonstrated that machine learning algorithms trained on wearable device data can differentiate good from poor cognition reasonably well. Such studies have laid the foundation for potentially using wearables as a first line of screening for cognitive impairments outside of clinical settings.

Many consumer wearables include functionalities to prompt behavioral changes that promote sleep quality; however, such prompts largely occur after poor sleep has already occurred. In a recent study, Sakal and colleagues demonstrated that wearable device data and machine learning can forecast sleep efficiency 4–8 h before sleep onset, opening the possibility of designing interventions that proactively prevent poor sleep before it occurs [58]. While proactive wearable-based sleep intervention research is in its infancy, current evidence holds promise that prevention need not be limited to diseases and mortality but can be extended to healthy lifestyle factors such as sleep.

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Chapter 2
A Review on Integration of Advanced Signal Processing Techniques for Wearable ECG Bio-Amplifiers: A Circuit Perspective

Reshma Karunanithi, Pandiyarasan Veluswamy, and Rohini Palanisamy

Abstract The development of wearable ECG monitoring systems is significantly influenced by advancements in biosignal processing, which ensures signal quality through effective noise reduction for real-time and continuous cardiac assessment. Key design considerations for these systems include the compatibility of the analog front end (AFE) with the wearable transducing medium, power consumption, battery life, and miniaturization. Among these factors, the AFE's compatibility plays a major role in determining the acquired signal quality due to the introduction of dynamic contact impedance. In wearable transducers, maintaining proper skin–electrode interface over time is challenging, often resulting in contact impedance exceeding 10 Megaohms, which directly impacts biopotential conductivity and signal quality. Therefore, wearable ECG monitoring necessitates the design of suitable amplifiers, focusing on advanced signal processing techniques to mitigate the effects of high contact impedance and ensure high-quality signal acquisition independent of the transducing medium. The systematic review of existing bio-amplifiers, highlighting key challenges and design requirements for wearable ECG monitoring devices is presented in this chapter. It examines strategies for improving signal quality, the implementation of noise reduction techniques and design requirements. Additionally, the analog and digital filtering techniques, which are essential for ECG signal processing are also discussed. Analog signal processing includes filtering techniques, such as low-pass, notch and high-pass filters, which are critical for removing baseline wander, powerline and high-frequency noises. Digital filtering techniques, including adaptive filtering and notch filters, eliminate high-frequency and powerline interferences, while advanced signal processing techniques are employed to separate noise from the acquired ECG signal. This chapter provides a comprehensive overview of the current state and future directions of bio-amplifiers in wearable ECG monitoring

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from a circuit perspective, offering insights into overcoming existing challenges and improving wearable ECG amplifier performance.

Keywords Wearable ECG amplifiers · Contact impedance · Advanced signal processing

2.1 Introduction

2.1.1 Wearable ECG Monitoring

Electrocardiography (ECG) is a non-invasive cardiac diagnostic technique used to record the electrical activity of the heart functions and events [1]. It plays a crucial role in the early detection of various cardiac dysfunctions, including arrhythmias, chronic cardiac conditions, and other underlying abnormalities [1, 2]. According to the World Health Organization (WHO), due to cardiac abnormalities, an estimated cardiac death mortality rate of about 17.9 million people in 2019 was recorded [3, 4].

In many cases, warning signs of cardiac dysfunction, such as adverse effects of drug dosage, physical activity and other harmful conditions including pollutant exposure from the surrounding environment, can manifest as cardiac events [1, 5]. Early detection of cardiac abnormalities is essential for reducing mortality rates and providing timely, effective interventions. Therefore, continuous monitoring of ECG is vital for early detection of these cardiac abnormalities in real-time.

Clinical ECG [2, 6] is the traditional method conducted in a clinical setting using a standard 12-lead electrode configuration. It offers high accuracy due to the use of multiple electrode placements and specialized signal processing units. These systems are primarily intended for targeted patients, with medical experts interpreting the results at specific time intervals to detect abnormalities by analyzing cardiac symptoms in clinical environment. However, clinical ECG has limitations in providing continuous monitoring, which is essential for the early detection of cardiac abnormalities.

Wearable ECG [7, 8] has revolutionized cardiac healthcare by enabling continuous and remote patient monitoring. These devices integrate advanced signal processing techniques to capture and analyze cardiac biopotentials, providing valuable insights into heart function outside of traditional clinical settings. Wearable ECG monitoring systems are designed for both targeted (cardiac patients) and non-targeted users, providing 24/7 continuous monitoring of cardiac events [9]. This enables early detection and timely response to cardiac abnormalities, thereby improving patient outcomes and facilitating personalized healthcare interventions.

Wearable ECG devices represent a significant advancement over clinical ECG techniques. While adhering to the fundamental principles of ECG, these devices offer several advantages, including standalone electrode configurations (three to single lead), portability, miniaturization, power optimization, integrated AI with advanced signal processing and user compatibility as shown in Fig. 2.1. These systems have a wide range of applications that extend beyond traditional clinical settings, making them vital tools for preventive and personalized healthcare [10, 11].

One of their primary uses is in arrhythmia detection, where they can capture irregular heart rhythms, such as atrial fibrillation and tachycardia, which are often unnoticed during short-term ECG exams [3]. The inclusion of real-time alerting features enhances emergency response, enabling quicker reactions during life-threatening events like cardiac arrest [12, 13]. Wearable ECG systems are particularly beneficial for geriatric care, where continuous monitoring helps detect abnormalities and ensures timely intervention [2, 9]. These systems are also invaluable for pre- and post-operative monitoring, allowing healthcare providers to remotely track cardiac

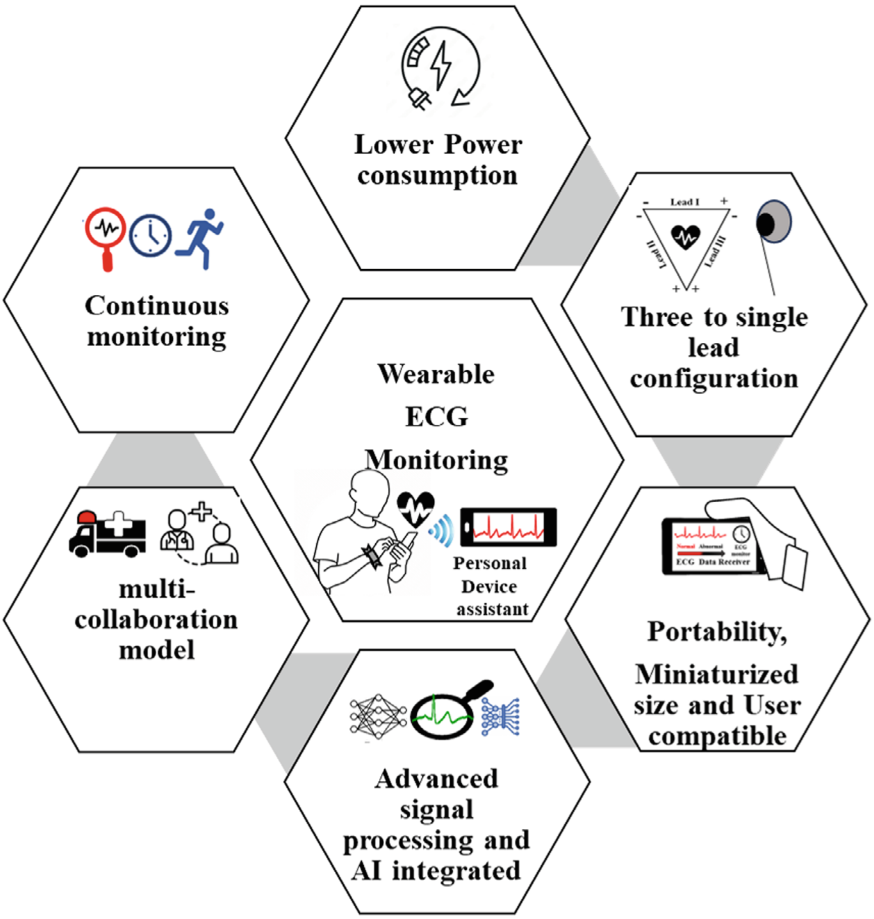


Fig. 2.1 Advantages of wearable ECG monitoring (*Sources* Microsoft PowerPoint Clipart)

recovery after surgeries like pacemaker implantations [4]. Additionally, they facilitate remote and home-based cardiac monitoring, offering better insights to patients with chronic heart conditions by reducing the need for frequent hospital visits.

In the realm of sports, athletes can use these devices for cardiac fitness monitoring, helping them optimize training intensity and detect signs of overtraining and cardiovascular stress [9, 14, 15]. Furthermore, clinical trials and medical research also benefit from these wearable ECG systems, as they allow collection of volume datasets over extended periods for research purposes, aiding in the study of disease progression and treatment efficacy. Additionally, non-targeted users including normal individuals who are willing to track their cardiac health can also benefit wearable ECG monitoring systems. Thus, the critical nature of these applications in wearable ECG monitoring, ensures the reliability and quality of acquired ECG signals through advanced signal processing techniques.

2.1.2 Process of Wearable ECG Monitoring: Overview

The process of wearable ECG monitoring can be broken down into three key stages as shown in Fig. 2.2: (a) signal acquisition, (b) signal processing, and (c) signal transmission/reception [16–19]. Signal acquisition is the initial stage in which ECG signals are captured and recorded through the interface called transducing medium. The core principle of ECG signal acquisition reflects the ionic current flow associated with the contraction and relaxation of cardiac muscles and nerves. Analyzing these signals helps individual users gain indirect insights into heart activities without the need for invasive procedures. The transducing medium used in ECG monitoring systems are electrodes, which acts as an interfacing medium between skin and the signal processing unit.

The wearable ECG signal acquisition prefers a standalone electrode configuration since it is designed for long-term, continuous monitoring and utilizes surface-mounted semi-dry and dry electrodes as the transducing medium [20–22]. The conductive polymer-based electrodes, highly conductive metal electrodes, surface

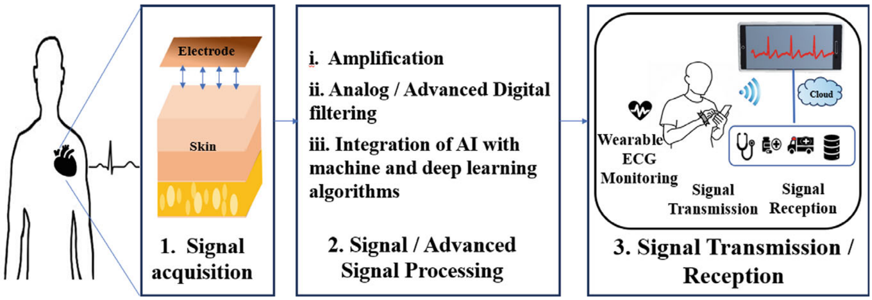


Fig. 2.2 Process of wearable ECG monitoring (*Source* Microsoft PowerPoint Clipart)

mounted non-contact electrodes, patch based, screen printed, e-tattoos, and self-adhesive electrodes are the different types of wearable transducers employed for ECG signal acquisition. These electrodes, often made from conductive materials and polymers, are more comfortable and suitable for prolonged wear, though they introduce challenges in signal acquisition at the skin–electrode interface.

The effectiveness of ECG monitoring systems depends on the quality of the acquired ECG signals, since it has inherently low amplitude/voltage signals, typically ranging from microvolts to a few millivolts. These signals are vulnerable to various forms of noise and interference, which can obscure essential information necessary for accurate diagnosis. The skin–electrode interface [23–26] plays a pivotal role in determining the effectiveness of the signal processing techniques employed. The interaction between the skin and electrodes influences how well the cardiac biopotentials are captured and transmitted to the Analog Front End (AFE) of the wearable device.

Figure 2.3 illustrates the factors affecting ECG signal acquisition in wearable applications [21, 27–34]. Additional factors such as sweat, skin type, temperature, pressure and body movements further complicate the ECG signal acquisition process in wearable systems. These variables need to be carefully considered when designing the signal processing unit to ensure high-quality and reliable signal output. The signal processing unit is the second stage of wearable ECG monitoring and includes amplification to convert the acquired low voltage ECG signal into a measurable voltage output. Further, filtering in both analog and digital domains is employed for noise reduction in wearable environments. As a result, it also plays a crucial role in wearable ECG monitoring systems, ensuring that the captured data is accurate, reliable, and interpretable.

Wearable ECG systems integrate advanced signal processing techniques for effective noise reduction, such as adaptive filtering, and incorporate AI, machine learning and deep learning algorithms for achieving precision in decision-making [35, 36]. Then, the processed ECG signal is further trans-received through wireless channel to a digital device for better visualization and interpretation of acquired cardiac output. This enables these systems to provide user-friendly, accessible solutions for continuous cardiac monitoring, for better decision making even in non-clinical environments.

2.2 Interferences in Wearable ECG Monitoring Systems: Sources and Their Effects

ECG signals are characterized as low voltage signals of few micro to millivolts with frequency ranges between 0–150 Hz [37–39]. Wearable ECG monitoring necessitates careful consideration of potential interferences that can affect signal acquisition and processing in wearable ECG devices since it can hinder accurate detection of cardiac abnormalities. There are various types of possible interferences that need to

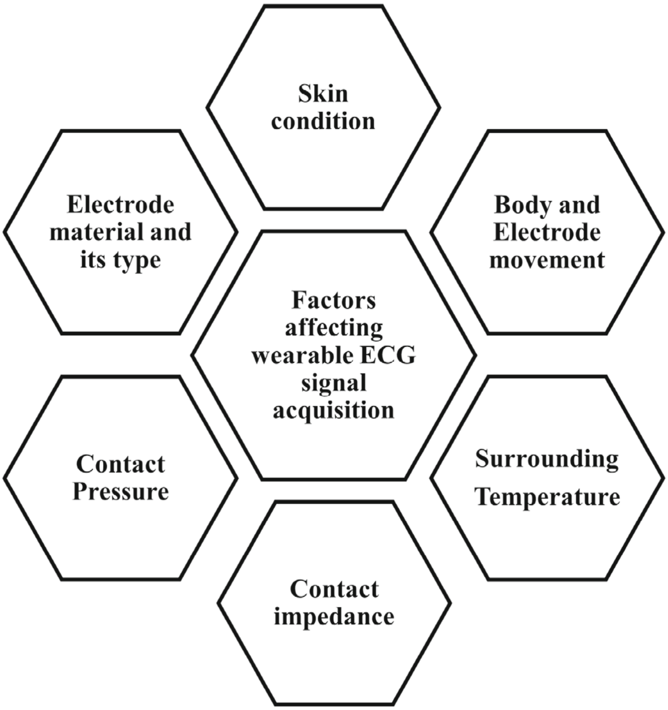


Fig. 2.3 Factors affecting ECG signal acquisition

be considered in developing the signal processing unit for wearable ECG monitoring are baseline wandering, powerline interference, muscle artifacts, impedance noise, amplification noise, motion artifacts, channel noise, and other composite noises as shown in Table 2.1 [40, 41].

2.2.1 Baseline Wandering in Wearable ECG

(i) DC Offset

In wearable ECG monitoring, baseline wandering is one of the predominant noises where it distorts low frequency components ranging between 0.05–1 Hz [12, 42]. Respiration, body movements and skin electrode impedance are the common factors that contributes baseline wandering and it is dynamically varying in terms of wearable ECG monitoring applications. Furthermore, DC offset needs to be carefully considered, as it can introduce a negative baseline shift that may lead to signal distortion and loss during subsequent processing. For instance, [16, 43] direct current potentials

(0 Hz) up to 200 mV level are generated, over which the small cardiac signal (typically 3–4 mV) is superimposed [44]. In order to amplify the signal without saturating the electronic components, it is necessary to eliminate this baseline artifact.

(ii) Baseline drift instability

The unstable and gradual drifts in ECG signal from its origin distort the visualization of morphological features especially ST segments and timing characteristics of acquired ECG signal. The very low frequencies (0.1–0.2 Hz) that cause the baseline wander which are generally attributable to periodic respiratory movements (15 respirations/min yields a cycle of 4 s and a fundamental component of 0.25 Hz). However, removing these low-frequency components may lead to distortion of the ST segment [36]. During bradycardia, the heart rate may drop to approximately 40 beats/minute, implying that the lowest frequency contained in the ECG is approximately 0.67 Hz

Table 2.1 Possible interferences in wearable ECG monitoring

Interferences	Visualization	Frequency	Causes	Effects
Baseline wandering	Baseline drift and Slow, gradual shift in baseline	0.05–1 Hz	Respiration, patient movement, electrode impedance	Drifts and instability in baseline, making it difficult to interpret ECG
Powerline interference	Sinusoidal waveform, consistent superimposed frequency	50 Hz	Electromagnetic coupling from power lines	Distorts ECG signal, obscuring true cardiac signals
Muscle noise	Rapid, irregular spikes and bursts	20–150 Hz	Muscle contractions, nearby electronic devices	Creates noise in the ECG, making it difficult to distinguish the true ECG features
Impedance noise	Low amplitude ECG signals with baseline, high frequency interferences	0.05–1 Hz/50 Hz	High contact impedance, poor shielding and contact	Signal amplitude attenuation and high frequency artifacts
Motion artifacts	Erratic, abrupt changes in waveform	0.1–10 Hz	Patient movement, electrode contact	Causes transient distortions, potentially superimposing true ECG events
Channel noises	Random, continuous noise	2.4–5 GHz	Wireless transmission of Signals lies within ECG frequency range	Introduces random noise, reducing signal-to-noise ratio

(continued)

Table 2.1 (continued)

Interferences	Visualization	Frequency	Causes	Effects
Amplification circuit noise	Background noise depicted with low SNR	1–50 Hz	Intrinsic and thermal noise	Low frequency signal degradation
Composite noises	Spikes and less accurate ECG signals depending on source	Wide range in ECG frequency	Electrical and electronic devices, environmental factors	Unpredictable noise, degrading overall signal quality

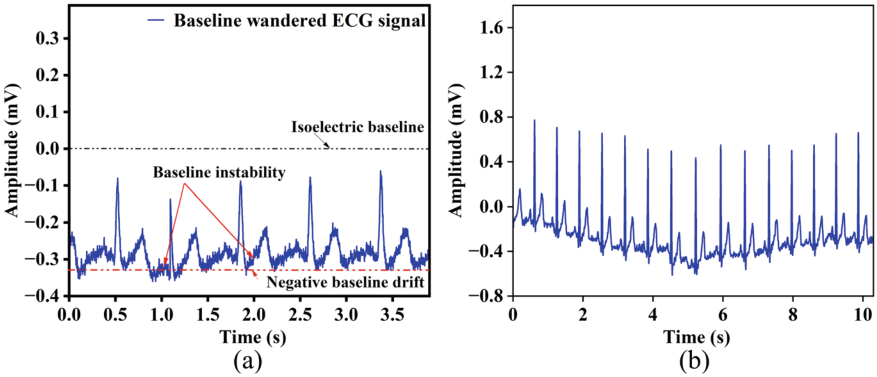


Fig. 2.4 (**a**) ECG signal with baseline wandering, (**b**) ECG signal with baseline instability

[44]. Further, it is necessary to choose a slightly lower cut-off frequency such as 0.5 Hz for effective filtering. If too high a cut-off frequency is employed, the output of the high pass filter contains an unwanted, oscillatory component.

Figure 2.4(a), and (b) illustrates the ECG signal with baseline wandering interferences as DC offset and baseline instability respectively. It is evident that the negative baseline drift of about −0.33 mV occurs due to DC offset voltage as shown in Fig. 2.4(a). During ECG signal acquisition, the impeded flow of this current creates a voltage drop that appears as a constant voltage. Further, the baseline instability is due to normal body movements which leads to minimum leakage current that flowing into the positive and negative terminals of the amplifier.

2.2.2 *Powerline Interference*

Powerline interference (PLI) is the most prevalent interference in wearable ECG monitoring, often arising from electromagnetic coupling of the powerline at 50 Hz in the acquired ECG signal [45, 46]. As the wearable ECG monitoring environment

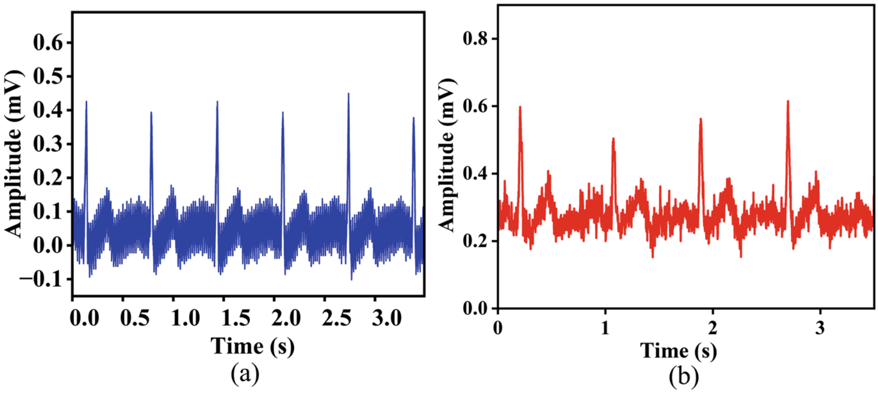


Fig. 2.5 (**a**) ECG signal with powerline interference, (**b**) Illustration of EMG noise in acquired ECG signal

is surrounded by powerlines, which cannot be restricted, it is more vulnerable than clinical ECG. Even with the amplifiers having high Common Mode Rejection Ratio (CMRR), residual PLI can still disrupt ECG recordings due to factors like electrode impedance differences and stray capacitance. The stray capacitance through the powerline and other nearby electrical equipment causes electromagnetic coupling which mainly contributes to power-line interference. It generates interference which is superimposed over acquired ECG signal. Thus, it also affects the accurate prediction of ECG signal characteristics and leads to false prediction of RR intervals which are used to evaluate heart rate. This interference can also distort the morphological characteristics of the P and T waves, potentially hindering accurate ECG analysis.

Residual PLI [47–49] can interfere with the correct delineation of ECG wave boundaries and disrupt the proper functioning of automated ECG analysis. Wearable systems are more vulnerable to PLI due to high skin-electrode impedance associated with flexible dry electrodes, which enhances coupling with ambient electromagnetic interference. This higher impedance can amplify the effects of external noise, including PLI. Poor grounding of the ECG system can also increase susceptibility to PLI. It can mask the ECG signal, making it difficult to detect ECG morphological features like the P-wave, QRS complex, and T-wave. This can lead to inaccurate diagnoses and compromised patient care (Fig. 2.5(a)).

2.2.3 Muscle Artifacts/Electromyography Noise

Electromyography/Muscle artifacts are high frequency interferences ranging from 20 to 100 Hz that obscure ECG signal quality [40, 41, 50]. Muscle contractions, particularly from muscles near the ECG recording site, generate electrical signals that can interfere with the ECG readings. This interference, known as electromyogram

(EMG) noise, introduces high-frequency noise into the ECG signal. The presence of this noise can obscure critical features of the ECG, such as the P-wave and T-wave, making it challenging to accurately interpret the cardiac activity. Figure 2.5(b) shows the illustration of EMG noise in acquired ECG signal. The amplitude of EMG noise over time is plotted. This shows that the overlap between muscle-generated signals and the ECG can significantly affect the quality and reliability of the data collected, especially in wearable ECG systems where movement is common.

2.2.4 Impedance Noise

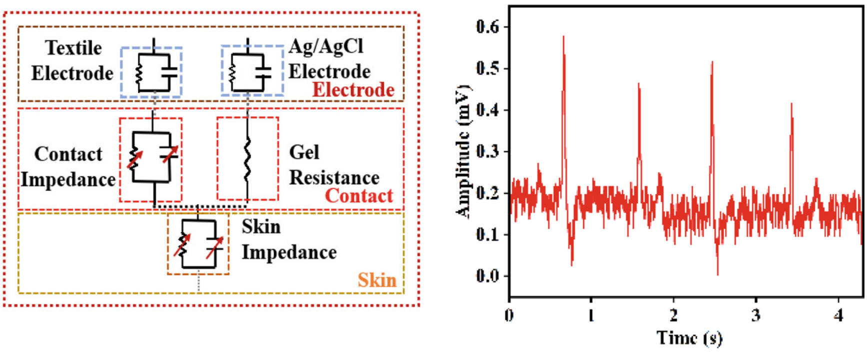
Impedance noise [23, 28, 33, 51, 52] is a significant concern in the design of wearable ECG monitoring systems. This noise arises from the dynamic variations of contact impedance at the skin–electrode (contact) interface. The quality of ECG signal acquisition depends on the characteristics of the contact interface. In clinical ECG monitoring, electrodes are typically in direct contact with the skin through the electrolytic gel, providing low impedance and enabling the measurement of voltage levels. However, wearable ECG systems often employ dry and semi-dry surface mounted electrodes, leading to varying impedance values based on the point of contact. Impedance is a combination of resistance and capacitance, and it can fluctuate dynamically due to changes in contact area. An increase in contact area leads to higher capacitance, which in turn reduces contact impedance and improves conductivity.

This ultimately results in a decrease in ECG voltage amplitude in wearable ECG signal acquisition. To address impedance noise, the advanced signal processing techniques need to be considered.

Figure 2.6(a) illustrates the equivalent circuit of contact impedance in surface mounted electrodes and Fig. 2.6(b) depicts the impedance noise in ECG signal while using dry textile electrodes. The impedance noise can be illustrated in terms of low amplitude, poor signal quality and fluctuations with baseline drifts. The dynamic high contact impedance of dry electrodes ranges from 1 to 5 $M\Omega/cm^2$ while semi dry electrodes have values of about 10 $k\Omega/cm^2$ as recorded by using equivalent circuit model [33, 52]. Further, the contact pressure applied on the electrodes is significant in determining the contact impedance such that contact pressure is inversely proportional to the contact impedance. Additionally, the factors like sweat and skin hydration affects the signal quality due to uneven electrolytic concentration leading to low conductivity at the skin–electrode interface.

2.2.5 Motion Artifacts

Motion artifacts in wearable ECG monitoring systems are distortions in the ECG signal caused by the physical movement of the individual user and the wearable

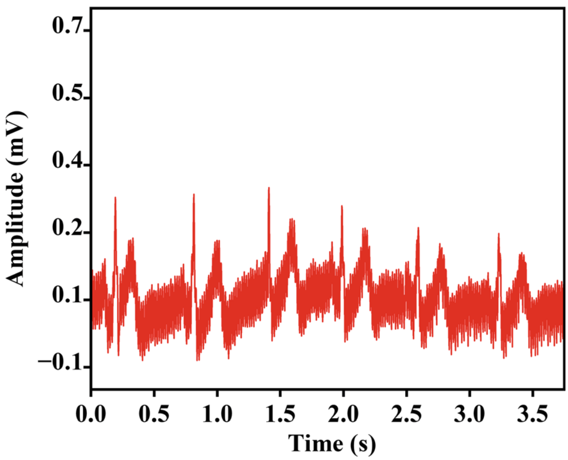


(a) (b)

Fig. 2.6 (**a**) Contact impedance at skin electrode interface, (**b**) ECG signal with impedance noise

device. These artifacts can significantly impact the quality of the ECG signal, leading to significant challenges in accurate cardiac monitoring. When the electrodes move relative to the skin, it can cause fluctuations in the electrode–skin impedance [40]. This movement may occur due to body movements, poor electrode adhesion in wearable devices. As the skin stretches and compresses during body movement, the mechanical stress on the skin can alter the contact between the electrode and the skin, leading to changes in the recorded signal as illustrated in Fig. 2.7.

Fig. 2.7 ECG signal with motion artifacts



2.2.6 Channel Noise

Channel noise in wearable ECG amplifiers, particularly due to wireless interference during signal transmission and within the amplification circuit, can significantly degrade the quality of the ECG signal [53]. This noise is a critical challenge in ensuring reliable and accurate ECG monitoring, especially in wearable devices that rely on wireless communication. Several wireless transmission technologies used for ECG signal acquisition with their causes of interferences are discussed.

1. **Wi-Fi**: It adheres to the IEEE 802.11 standard, operating in the 2.4 and 5 GHz bands [54]. It offers high data rates from 72 Mbps (Wi-Fi 4) to 9.6 Gbps (Wi-Fi 6). Although Wi-Fi offers a range of about 50–100 m indoors and the ability to support high-bandwidth applications are significant advantages, its higher power consumption makes it less suitable for compact wearables. Wi-Fi mostly employs orthogonal frequency division multiplexing, which produces complex noise patterns due to multiple subcarriers transmitting simultaneously. When the ECG system is close to Wi-Fi proximity route it introduces interference as periodic high frequency artifacts. Further the high power of Wi-Fi (greater than or equal to 100 mW) can cause stronger electromagnetic interference during ECG signal trans-reception [40, 41, 55].
2. **Bluetooth**: Bluetooth Low Energy (BLE) is the most commonly used wireless technology in wearable ECG devices [10, 40, 54]. Bluetooth operates under the IEEE 802.15.1 standard with 2.4 GHz ISM band, supporting data rates up to 3 Mbps. It is designed for ultra-low power consumption, follows Bluetooth 4.0 and later versions including Bluetooth 5.0 which is highly energy efficient, with data rates ranging from 125 kbps to 2 Mbps. BLE has range typically spans about 10–50 m but can reach up to 200 m with Bluetooth 5.0. Its energy efficiency makes it ideal for continuous transmission of ECG data while preserving battery life, making it preferable in wearable ECG monitoring applications. However, the bluetooth enabled ECG monitoring systems uses gaussian frequency shift keying for data transmission which tends to have less spectral spreading than Wi-Fi, and the low transmission power of about 1–10 mW causes less interference than Wi-Fi. Due to frequency hopping nature of bluetooth, interference appears in acquired ECG signal as noise bursts and can be easily removed by advanced filtering methods.
3. **Zigbee**: Based on the IEEE 802.15.4 standard, Zigbee is another low-power option for wearable ECG systems. It supports low data rates of up to 250 kbps and operates in the 2.4 GHz band globally [56]. The primary strength of this network lies in its support for mesh networking, allowing devices to relay data across extended ranges, typically from 10 to 100 m. Zigbee uses offset quadrature phase shift keying modulation and direct frequency spread spectrum with lower power consumption data transmission. Since it is a multi-device network where several devices transmit data simultaneously, it causes high frequency interference with lower amplitude compared to bluetooth and Wi-Fi in the acquired ECG signal.

4. **Cellular technologies**: It includes 4G (LTE) and 5G systems which operate across a broad range of frequencies, including sub-6 GHz and millimetre-wave (mm Wave) bands for 5G. Cellular networks provide extensive coverage and high data rates of up to 20 Gbps in 5G [41, 56, 57].

Radiative interference arises when the ECG system picks up electromagnetic fields emitted by cellular devices, while conductive interference occurs if the power supply and ground share pathways with cellular communication circuits. Hence the interferences arise in terms of baseline drift and high frequency artifacts. When the ECG monitoring system is close to a cellular device (such as a smartphone), interference occurs, especially during active communication like phone calls or data transmission.

2.2.7 Amplification Circuit Noise

Within the amplification circuit of the wearable ECG device, various factors can introduce noise [49, 58–60]. These include thermal noise from resistive components, noise from the power supply, and electromagnetic interference (EMI) from nearby electronic components and devices. This noise can be amplified along with the ECG signal, leading to a lower signal-to-noise ratio (SNR). Amplification circuit noise can manifest as low-level continuous noise, baseline drift and even high-frequency oscillations that overlay the ECG signal. This makes it challenging to distinguish between true cardiac events and noise, particularly in low-amplitude signals such as those from the P, Q and T-waves.

2.2.8 Composite Noises

Composite noises in wearable ECG systems are the result of multiple noise sources that collectively degrade the quality of the ECG signal. These include thermal noise, triboelectric noise, temperature-dependent noise, and mechanical vibration noise [40, 41].

(i) Thermal noise arises from the intrinsic thermal activity within resistive components of the ECG device, such as resistors, transistors, and operational amplifiers. This type of noise introduces a random, low-level disturbance across all frequencies, which can obscure the finer details of the ECG signal, particularly during the amplification process. In textile-based ECG systems, triboelectric noise occurs due to friction between different materials, such as the movement of textile electrodes against the skin and clothing. This friction generates triboelectric charges, causing sudden spikes and fluctuations in the ECG signal, especially during movement, leading to misinterpretation of heart activity.

(ii) Temperature-dependent noise [8] results from variations in ambient temperature or the temperature of the wearable device itself, which can alter the electrical characteristics of components. This can lead to drift in the acquired ECG signal, particularly in the baseline and during periods of low signal amplitude.
(iii) Mechanical vibration noise is caused by external vibrations, including operating machinery and walking on uneven surfaces, which can transfer to the wearable ECG device. This noise causes rhythmic, periodic disturbances in the ECG signal, potentially mimicking physiological abnormalities like arrhythmias, leading to misinterpretation.

2.3 Existing Wearable ECG Amplifiers

Wearable ECG amplifiers [7, 21] play a crucial role in the design of ECG monitoring systems by capturing and amplifying weak bioelectrical signals from the heart to an measurable output range. The evolution of bio-amplifiers in wearable ECG monitoring systems is driven by two key factors including the advancements in signal processing techniques and the significance of continuous cardiac health monitoring. Early ECG bio-amplifiers relied on bulky and power-consuming vacuum tubes. These were prone to noise and impractical for wearable applications. However, the introduction of transistors in the 1950s marked a significant improvement. Transistors were much smaller and more efficient, offering a significant reduction in power consumption compared to vacuum tubes. The development of integrated circuits (IC) in the 1960s and 1970s further revolutionized bio-amplifier design. ICs allowed for the integration of multiple components onto a single chip, leading to significant reductions in size, power consumption, and cost. This paved the way for the development of more sophisticated and portable ECG monitoring systems. By overcoming limitations in size, power consumption, noise, and accuracy, modern bio-amplifiers have enabled the creation of wearable and reliable devices for continuous heart health monitoring. The generations of ECG bio-amplifiers are classified based on the signal processing techniques as: (a) IC using operational amplifiers, (b) IC using instrumentation amplifier and (c) Integrated analog front end (Fig. 2.8).

2.3.1 Major Design Parameters that Need to Be Considered in Wearable ECG Amplifiers

For optimal performance in wearable applications, bio-amplifiers need to be developed by considering key design parameters for hardware solutions as discussed below:

(a) Input Impedance

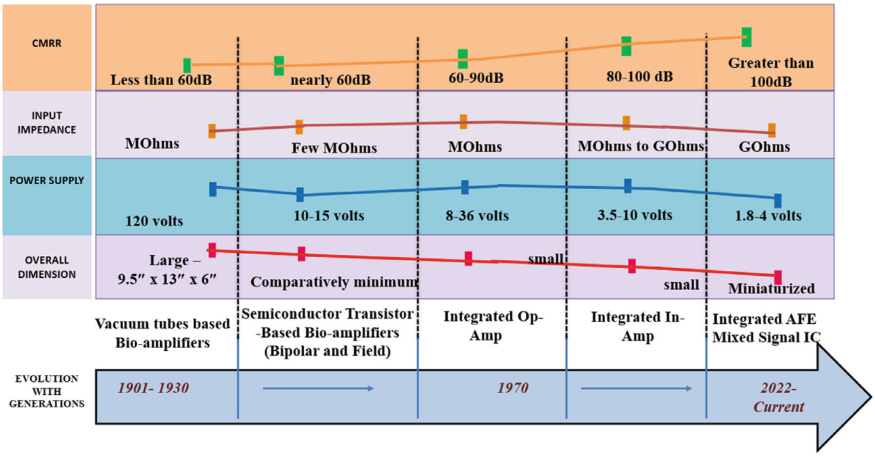


Fig. 2.8 Evolution of wearable ECG amplifiers

Input impedance [52] is one of the significant parameters in wearable ECG monitoring applications since it directly affects the acquired ECG signal while employing wearable transducing medium especially surface mounted dry electrodes. It refers to the source impedance between the input terminals of the ECG amplifier and the ground. The input impedance of the amplifier is given in (2.1) as the complex sum of resistance and capacitance.

$$z_{in} = R_A + jC_A \tag{2.1}$$

where Zin is the input impedance, R_A is the resistance of the amplifier and C_A is the capacitance of the designed amplifier. The contact impedance between the electrode and skin is high for surface mounted dry electrodes, which leads to significant reduction in ECG signal voltage across this impedance. Low input impedance of the amplifier causes signal attenuation in the recorded ECG signal due to loading effect, where the amplifier draws current from the high-impedance electrode-skin interface, reducing the signal amplitude. Hence, high input impedance ranging from 10 MΩ to several GΩ is essential to ensure minimal loading on the electrodes to attain reliable ECG signal.

(b) Input Bias Current:

The input bias current [33] is the minimal leakage current that flows into the input terminals of the amplifier due to internal electronic circuits. Low bias current ensures minimal leakage current through the electrode interface. The input bias current ranging from 1 nA to few pA is preferred in wearable ECG amplifiers, since it otherwise leads to baseline drift with high voltage offsets when high contact impedance prevails.

(c) Common Mode Rejection Ratio (CMRR)

CMRR [6] is the ability of the amplifier to amplify the differential signals with common mode noise rejection. The common mode signals indicate the unwanted noise signals while differential signals represent the acquired ECG signal.

$$CMRR = 20 \log \frac{|A_d|}{|A_{cm}|}. \tag{2.2}$$

where A_d is the differential gain (amplification of the desired signal difference), while A_{cm} is the common-mode gain (amplification of noise common to both inputs). The CMRR is the ratio of differential mode signal to the common mode signal as given in (2.2). In wearable ECG monitoring applications CMRR of about 80–120 dB is widely employed in amplifier design for effective common mode rejection with high SNR, since the electrodes employed in ECG signal acquisition result in high contact impedance.

(d) Gain

Gain [6, 8, 32, 61] is the ratio by which input signal gets amplified is given in (2.3) and is usually determined by an external resistor. The proper gain selection and adjustment are essential in wearable ECG monitoring applications to enhance acquired low amplitude signals with high SNR, since these systems are prone to motion artifacts and contact impedance variations. Thus, a common gain range of 54 dB to 60 dB is employed in most of the wearable ECG amplifiers.

$$Gain = 20 \log \frac{[V_{out}]}{[V_{in}]} \tag{2.3}$$

where V_{out} is the output voltage and V_{in} is the input voltage of the ECG amplifier and is determined by setting the external resistor.

(e) Power supply and consumption

Power supply [42, 62, 63] is the input power required to process the ECG signal. In wearable applications, the power supply is low, with common voltage rating rangings between 3–5 V. Further, micro-powered ECG monitoring systems are also employed based on the applications. Power consumption is the total power consumed for ECG signal acquisition per hour and it determines the battery life in idle and active mode. Thus, optimal power consumption ensures the effective performance and reliability of wearable ECG amplifiers.

2.3.2 *Characteristics of Commercially Available ECG Amplifiers*

Several commercial amplifiers are available offering distinct features and specifications for wearable ECG monitoring applications. This review highlights some of the most widely used wearable ECG amplifiers, focusing on their key specifications and characteristics.

(i) **Analog Devices**:

(a) **AD52x**: AD520 [64] is the high-performance ECG bio-amplifier of AD52x family and is designed using monolithic instrumentation amplifiers which is introduced by Analog Devices in 1971. It is in the form of an IC and supports gain ranges between 1–1000. However, it has CMRR of about 86 dB and requires high power supply voltage range of −15 to 15 V which adds complexity in wearable applications.

(b) **AD620**: It is the improved version of the AD52x family which is low-cost, high-performance instrumentation amplifier with low supply voltage of ±2.3 to ±18 V, offering flexibility in wearable ECG monitoring. The adjustable gain ranges from 1–10,000 with high input impedance of 10 GΩ, resulting in high-precision ECG signal output. The low input bias current (1 nA) ensures minimal interference with weak ECG signals, while the CMRR of 120 dB allows for effective common mode noise rejection. Further, it is laser trimmed and the power consumption is in range of milliwatts, making it one of the most preferred amplifiers in wearable ECG monitoring [65].

(c) **AD8232**: The AD8232 from Analog Devices is a low-power, single-lead ECG monitoring IC which is well-suited for heart rate detection and fitness wearables. With a high input impedance of over 10 GΩ and low power consumption of about 170 μW, it offers advantages in battery powered wearable ECG monitoring applications. This amplifier includes built-in signal processing features to remove low and high frequency artifacts.

(d) **LTC2050**: It is a high precision, zero offset voltage operational amplifier designed for ECG monitoring applications requiring efficient DC performance. It features a low offset voltage of 0.5 μV ensuring accurate ECG recordings and stability over temperature variations. It has high CMRR more than 130 dB, providing effective noise rejection. The LTC2050 offers high voltage gain, low noise, fast settling time, rail-to-rail output, and low power consumption. Hence it is preferred in cardiac fitness related ECG monitoring applications [66].

In later generations AD822, AD8422 and ADPD1080 have been developed with improved CMRR with low power consumption. However these amplifiers belong to ADux series and have fixed impedance which affects SNR of acquired ECG signal since the wearable ECG electrodes have dynamically varying contact impedance.

(ii) **Texas Instruments**

The **ADS1298** [7, 10] is a high-performance multi-channel ECG amplifier which offers 8 channels, each with a fully integrated 24-bit delta-sigma analog-to-digital converter. The CMRR of 110 dB and input impedance greater than 10 GΩ ensure minimal signal loading with effective common-mode noise rejection. The ADS1298 includes operational features like lead-off detection, internal RLD, and DC lead-offset correction, which enhance reliability in wearable ECG monitoring. This multichannel configuration is widely used in ambulatory monitoring, and advanced research applications, however it consumes high power compared to other wearable ECG amplifiers.

The **ADS1292R** is a low-power ECG amplifier designed for ECG and other bio-potential measurements. It offers 2 differential and 3 single-ended input channels, making it versatile for wearable ECG monitoring configurations. With an input impedance of over 10 GΩ and CMRR of 120 dB, this amplifier offers high signal fidelity in wearable environments. The integrated right-leg drive (RLD) amplifier enhances signal quality by reducing common-mode noise but its relatively high-power consumption limits ultra-low power wearable ECG monitoring applications.

Similarly, Texas Instruments developed ADS1000-1, ADS119X, HDC1080 and INA333, which are preferred in biopotential measurements since they have low input bias current in picoamperes with low spectral noise. However, they are limited in wearable ECG monitoring, due to high power consumption.

(iii) **Maxim Integrated**

The MAX30003 [67] by Maxim Integrated/Analog Devices is an ultra-low power, single channel ECG amplifier designed specifically for continuous wearable ECG monitoring. It requires a low supply voltage ranging from 1.1 to 1.8 V with power consumption in microwatt range. The CMRR of about 100 dB and high input impedance greater than 500 MΩ enhance noise reduction during long-term monitoring. It is more suitable for fitness trackers, smart watches and non-targeted ECG monitoring applications since the single lead configuration limits more précised ECG recordings in wearable applications.

MAX4194 and MAXREFDES103 belong to MAXxx series offer features such as low noise, high CMRR, and adjustable gain, making them suitable for monitoring. However, the high-power consumption limits battery operated wearable ECG monitoring applications [68]. Hence the commercial amplifiers are designed based on IEC standards, however the dynamically varying high contact impedance and power optimization needs to be considered for better cardiac insights. Application specific wearable ECG amplifiers are developed and focus on improving the wearable system by addressing specific design parameters.

2.3.3 Application-Specific ECG Amplifiers

To address specific challenges encountered in wearable bio-signal acquisition including impedance noise and power constraints, some notable innovations in application-specific ECG amplifiers include:

(a) **Common Mode Suppression Bio-Amplifiers Based on CMRR** [69, 70]: These amplifiers are designed to enhance the common-mode rejection ratio

(CMRR), effectively reducing noise originating from electromagnetic interference (EMI) and powerline disturbances. By optimizing CMRR, the signal quality is improved, enabling more accurate detection of cardiac events. Power consumption and optimization are not addressed in these types of bio-amplifiers, which need to be considered in wearable ECG monitoring applications.

(b) **Micro Power High-Performance Bio-Amplifiers** [71]: These amplifiers focus on minimizing power consumption while maintaining high performance. Low-power designs are crucial for wearable and portable ECG devices where applications rely on battery life and external charging. Such amplifiers integrate power-efficient circuitry that ensures long-term monitoring without frequent recharging. However, dynamically varying contact impedance and the trade-off between power and signal quality are not addressed.

(c) **Negative Impedance Bio-Amplifiers for High Contact Impedance** [52, 72]: High skin–electrode impedance is a common issue in wearable ECG systems, often resulting in poor signal quality. Negative impedance amplifiers are used to compensate for this by effectively lowering the apparent impedance at the electrode interface, improving the overall signal acquisition. However, circuit design aspects including parameters such as high contact impedance and power optimization remain unaddressed.

(d) **CM Amplifier (CMA) Designs with Duty-Cycle Resistance** [10]: The incorporation of duty-cycle resistance and other adaptive techniques in CMA designs enhances the suppression of common-mode signals, thus ensuring better signal fidelity. These designs allow for more flexible filtering and improved noise reduction under varying conditions. However, design complexity increases due to precise circuit requirements and accurate calibration of the duty cycle.

(e) **High Input Impedance Bio-Amplifiers for Textile Electrodes** [15, 75]: Amplifiers with very high input impedance in the giga-ohm range are used for applications involving textile electrodes where contact with the skin is less stable. These designs help in preserving the signal integrity by reducing the loading effect caused by high electrode impedance. However, it is challenging to ensure stability across different operating conditions such as changes in humidity and temperature. Hence, proper selection of filter components and stable filter design are required to maintain consistent performance.

(f) **Right-Leg Driven Bio-Amplifiers for Noise Cancellation** [76]: Integrating right-leg driven circuits with bio-amplifiers enhances the ability to cancel common-mode noise, especially in scenarios with high environmental noise levels. This approach improves the signal-to-noise ratio, making it suitable for wearable applications in dynamic environments. However, this circuit is limited in dynamic environments due to potential instability, sensitivity to skin–electrode variability and power consumption.

Table 2.2 summarizes the performance of some of the notable application specific amplifiers. These application-specific designs demonstrate how tailored approaches in amplifier technology can optimize ECG signal acquisition for wearable and biomedical devices, enabling more accurate and reliable cardiac monitoring.

Table 2.2 Performance comparison of some of the application-specific bio-amplifiers

Key parameters	Maji et al. [71]	Guermandi et al. [76]	Dange et al. [73]	Kim et al. [15]	Mistretta et al. [70]	Chi et al. [74]	Spinelli et al. [75]
Lead wires	3	3	3	2	3	4	2
Implementation type	Discrete	ASIC	ASIC	ASIC	Discrete	ASIC	Discrete
Gain	100	1000	100	100	110	100	Unity AFE
Input impedance (0.1–150 Hz)	1 TΩ	45 fF	6.7 GΩ	10 GΩ	10 GΩ	60 fF	71 fF
CMRR (dB)	78	110	86	120	84	82	92
Noise (μVpp)	49 (0.1–150 Hz)	17.3 (0.5–100 Hz)	4.42 (0.5–100 Hz)	3.8 μVrms	32 250 Hz	45 nV/$\sqrt{\text{Hz}}$ (1 kHz)	71.9 nV/$\sqrt{\text{Hz}}$
Supply	7.5 μW	200 nW	60 μA	12.7 μW	130 μW	1.8 nW	25 mW

2.3.4 Challenges in Wearable Circuit Design: Key Limitations of Existing Wearable ECG Amplifiers

When designing the wearable ECG amplifier there are several design parameters that need to be considered, while existing ECG monitoring amplifiers are limited with their specifications. These include dynamically varying contact impedance, trade-off between power and signal quality, loading effect and power consumption. Many existing ECG amplifiers do not meet the desired threshold of 10 MΩ and higher, particularly while employing dry electrodes which exhibit high skin-electrode contact impedance. This inadequacy can lead to signal attenuation in the acquired ECG signals. Additionally, noise performance is affected by high levels of thermal noise, flicker noise, and EMI degrading the SNR [49]. These noise issues obscure low amplitude ECG signals, making it difficult to detect critical cardiac events such as arrhythmias.

Another significant limitation is achieving CMRR of greater than 100 dB, which is vital for rejecting noise from power lines and other common-mode sources. A CMRR below 80 dB can introduce substantial common-mode interference into ECG recordings, thereby obscuring accurate detection of cardiac signals. In addition, power supply remains a crucial challenge, as many existing systems demonstrate inadequate power supply rejection ratio, leading to performance degradation under supply voltage fluctuations. These variabilities can introduce noise and drift in the ECG signal, degrading signal stability during long-term ECG monitoring. Addressing these circuit design challenges is essential for enhancing the accuracy and reliability of wearable ECG amplifiers in continuous health monitoring applications.

2.4 Filtering and Advanced Signal Processing in Wearable ECG Amplifiers

2.4.1 Analog Filtering in Wearable ECG Signal Processing

Analog filtering techniques are used to remove unwanted noise and artifacts, ensuring signal quality in terms of high SNR and accuracy. In wearable ECG amplifiers, they are used to shape and refine the raw ECG signal in the analog domain. They are classified based on their element type and frequency characteristics as shown in Fig. 2.10. Active and passive filters play essential roles in analog signal processing for wearable ECG monitoring systems (Fig. 2.9).

Active filters utilize components such as operational amplifiers and transistors, providing enhanced control over the frequency response of the filter and facilitating the implementation of complex filter designs. One significant advantage of active filters is their ability to achieve frequency shaping, enabling precise attenuation of unwanted frequencies and achieving a sharper cutoff between the passband and

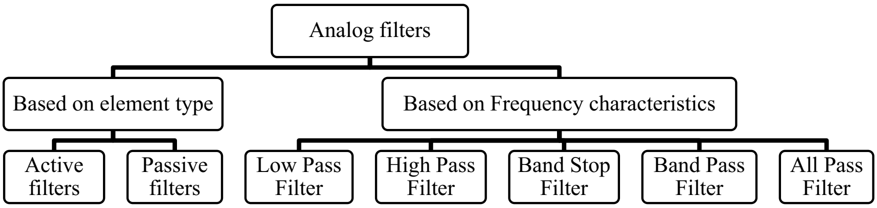


Fig. 2.9 Types of analog filters

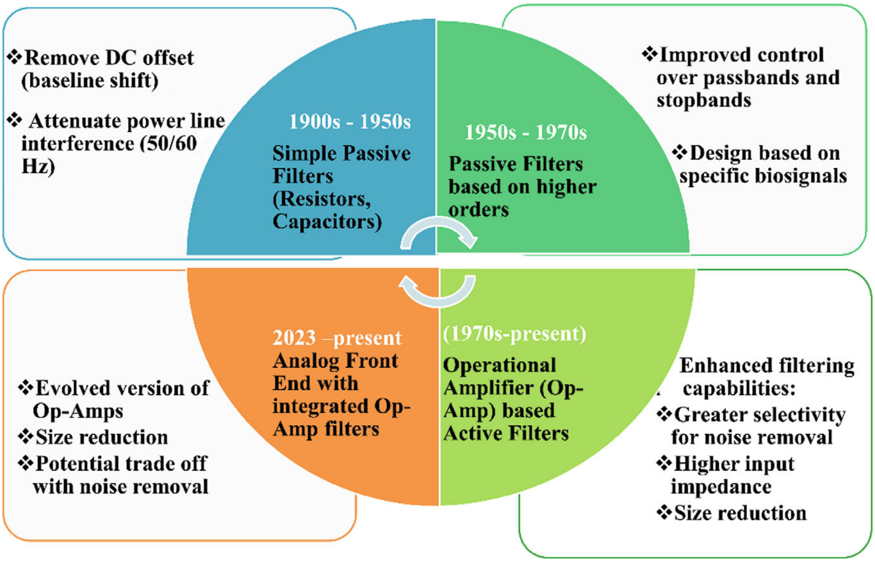


Fig. 2.10 Evolution of analog filters in wearable ECG monitoring

stopband. Active filter designs can incorporate multiple feedback paths and cascaded stages, which further support the realization of complex transfer functions optimized for steeper roll-off characteristics. Additionally, active filters can implement higher-order designs (typically 4th order and above), resulting in steeper roll off compared to lower order filters. The presence of additional poles in a higher order transfer function of the designed filter results in more rapid attenuation of frequencies outside the desired range.

Passive filters, in contrast, are composed of resistors, capacitors, and inductors, and generally exhibit slower roll-off characteristics compared to active filters. However, under certain conditions such as appropriate selection of cutoff frequency and filter order, passive filters can achieve relatively steeper roll-offs. While passive filters face limitations in attaining high-order designs due to the need for additional components interaction, combining multiple passive filter stages can create a higher-order response. Each additional stage enhances the overall order of the filter, thereby increasing the steepness of the roll-off. Passive filters depend on reactive components such as capacitors to shape their frequency characteristics. The inclusion of capacitance in wearable ECG monitoring can lead to higher roll-off rates, in low and high pass filtering. However, the roll off achieved through passive filtering is not as steep as that of active filters.

The filter characteristics of passive components limit the effectiveness of these filters in achieving steep roll-off and sharp cutoff region. Specifically, passive filters lack amplification capabilities, leading to more gradual attenuation of unwanted ECG frequencies. Figure 2.10 shows the performance with evolution of analog filters as discussed. In conclusion, although both active and passive filters can be employed to produce steeper roll-offs, active filters are preferred due to their amplifying components and higher-order designs can be implemented with less complexity. While passive filters can attain steeper roll-offs through multi-stage configurations, this increases circuit complexity and limits overall gain.

Various analog filter [77, 78] designs based on frequency of the interferences in wearable ECG signal, including the low-pass, high-pass, and notch filters, are preferably employed. To observe the performance of designed analog filters, the respective frequency spectrum is obtained by taking the Fast Fourier Transform of the filtered output.

(a) High Pass Filter

The amplified output signal has low-frequency noise and artifacts like baseline wandering in the range of 0.05–1 Hz, affects the recorded ECG signal. In wearable ECG monitoring DC offset of a few hundred millivolts is acquired with the amplified ECG signal that needs to be attenuated. The high pass filter is employed to remove these low frequency disturbances, and DC offset voltage in the acquired ECG signal [79].

(b) Low Pass Filter

The ECG frequency lies within the range of 0–250 Hz, in order to bandlimit the ECG signal and remove high frequency interferences above 250 Hz, a LPF is employed. In wearable ECG monitoring, active and passive filter designs are preferred based on application requirements and power consumption.

(c) Band Stop/Notch Filter

The notch and bandstop filter are used to remove the 50 Hz component from the acquired ECG signal. This filter combines the characteristics of both a low-pass and a high-pass filter, arranged in parallel, with their cutoff frequencies set at approximately 50 Hz. The system achieves better performance by incorporating both negative and positive feedback mechanisms around the operational amplifier. It is implemented as second order bandstop filters using either passive twin-T networks (double notch) or active circuits with feedback mechanisms to achieve high quality attenuation. The sharp attenuation at 50 Hz needs to be achieved to minimize distortion to other frequency components of the ECG signal.

Table 2.3 Comparison of performance of active analog filter designs

Feature	Sallen-key Low-Pass Filter (LPF)	Multiple feedback Band-Pass Filter (BPF)	State-variable filter (multipurpose)
Function	Sharper roll-off compared to passive RC LPF	Offers variable bandwidth and center frequency control	Provides high-performance filtering characteristics
Advantages	Sharper roll-off compared to passive RC filters. Higher output impedance	Adjustable bandwidth and center frequency. Can achieve steeper roll-off	Highly versatile, can be configured for various filter types. Offers superior performance
Disadvantages	Requires additional components (op-amp). More complex design	More complex design compared to basic RC filters. Requires careful component selection and tuning	Most complex design of the three. Requires in-depth filter design knowledge

Some additional analog filter designs used in wearable ECG monitoring are shown in Table 2.3. These filters are designed focusing on specific noise reduction and circuit complexity. Hence, based on the ECG signal requirements the analog filters can be designed.

2.4.2 Design Parameters to Be Considered for Analog Filter Design

The cutoff frequency, filter order, and arrangement of filters are vital factors in analog filtering for wearable ECG monitoring since they directly influence the filter performance, enhancing signal quality and reducing noise.

(i) **Cutoff Frequency**: The choice of cutoff frequency determines the range of frequencies that are attenuated or passed through by the filter. The cutoff frequency is calculated using (2.4), where f_c is the cutoff frequency, R is the resistance and C is the capacitance of the filter.

$$f_c = \frac{1}{2\pi RC} \tag{2.4}$$

In wearable ECG monitoring, it is essential to set cutoff frequencies appropriately to preserve the frequency components of the ECG signal while eliminating unwanted noise. In practice, a high-pass filter with a cutoff frequency around 0.5–1 Hz can effectively remove baseline wander, while a low-pass filter attenuates high-frequency noise without distorting the signal's higher harmonics.

(ii) **Filter Order**: The order of the filter dictates the steepness of the roll-off around the cutoff frequency. Higher order filters provide a sharper transition between the passband and the stopband, resulting in more effective attenuation of unwanted frequencies. The second-order filter with a slope of 40 dB offers better noise reduction compared to a first-order filter of about 20 dB [44]. However, higher order filters can introduce more phase distortion and may require more complex circuit designs, which could impact the size and power consumption in wearable applications.

(iii) **Arrangement of Filters**: The sequence in which different types of filters (high-pass, low-pass, notch) are arranged affects the overall filtering performance [40]. A common approach in ECG monitoring is to cascade a high-pass filter to remove baseline wander, followed by a notch filter to eliminate power-line interference, and a low-pass filter to attenuate high-frequency noise. This arrangement ensures that each type of noise is addressed to get optimum filter output, thereby improving the SNR while maintaining the integrity of the ECG waveform.

The narrow cutoff region and linear phase transition are important to preserve the morphological (P, Q, R, S and T) and timing characteristics of the ECG waveform. Significant amplitude distortion and phase shifts can alter the filtered ECG signal and affect accurate interpretation. These characteristics are primarily governed by the appropriate selection of filter order and cutoff frequency during the design process. In addition, factors such as temperature stability, component tolerance, and precision play a crucial role in ensuring consistent filter performance. These factors enable the analog filtering stage in wearable ECG systems to effectively enhance signal quality. Implementing filtering in the analog domain is particularly important for maintaining signal integrity prior to digitization, as it reduces noise and interference at an early stage. This also helps to reduce the complexity of digital signal processing units ECG monitoring systems.

2.4.3 Digital Filtering in Wearable ECG Signal Processing

The filtered analog output is converted into digital signal using ADC converter. However, during the analog-to-digital conversion process, noise and interferences such as powerline interference, and high-frequency noise can still affect the ECG signal. Therefore, digital filtering is required to further suppress these artifacts and enhance signal quality for precise analysis, while analog filters are employed for signal accuracy and interference attenuation in the analog domain. The two predominant types of digital filter design employed are time domain and frequency domain filters. This section focuses the impulse response based digital filters in wearable ECG monitoring. They include Infinite Impulse Response (IIR) filters, Finite Impulse Response (FIR) filters, and adaptive filters.

IIR Filters

IIR filters [18, 80] are digital filters in which the output depends on both current and past input samples as well as previous output samples due to feedback. Based on frequency response characteristics, IIR filters are classified into Butterworth, Chebyshev, Elliptic, and Bessel types. The choice of filter depends on the specific requirements of ECG signal processing, and their comparative characteristics are presented Table 2.4. Butterworth filters provide a maximally flat magnitude response in the passband, ensuring minimal amplitude distortion. Chebyshev filters achieve a sharper transition band at the expense of passband ripple. Elliptic filters offer the highest selectivity with the steepest roll-off, allowing ripples in both passband and stopband. In contrast, Bessel filters are characterized by a maximally flat group delay, resulting in minimal phase distortion and preservation of ECG waveform morphology.

The feedback mechanism with infinite impulse response makes the filter more efficient in achieving a desired frequency response. The significant advantage of IIR filters is their sharper roll-off characteristics and steeper attenuation in frequency response. This makes them effective for wearable ECG monitoring applications where rapid response to frequency changes is critical to accurate cardiac outputs. Furthermore, IIR filters generally require fewer filter coefficients (lower filter order) to reach a desired frequency response, resulting in reduced memory and computational requirements. However, IIR filters can introduce phase distortion, which is a significant consideration in ECG applications that require accurate representation of the cardiac signal. Furthermore, the feedback mechanism adds potential instability to the filter design when the filter coefficients are not chosen properly.

Table 2.4 Comparison of IIR filters

Characteristics	Butterworth	Chebyshev	Elliptical	Bessel
Passband response	Maximally flat (maximally smooth within the passband)	May have ripples within the passband	May have ripples in both passband and stopband	Maximally flat (similar to Butterworth)
Stopband attenuation	Gradual roll-off	Faster roll-off than Butterworth (for a given filter order)	Fastest roll-off (for a given filter order)	Slower roll-off than Butterworth
Design complexity	Simplest design (requires least number of components)	Moderate complexity	Most complex design	Moderate complexity
Phase response	Reasonably linear within the passband	Non-linear phase response	Non-linear phase response	Most linear phase response

FIR Filters

FIR filters [44, 81] use only present and past input values to determine the current output, which results in a finite duration of impulse response. This characteristic leads to the output settling after a finite number of input samples, contributing to the inherent stability of FIR filters. FIR filters exhibit predictable behaviour, making them suitable for applications where stability is critical, since they do not rely on feedback mechanisms. Additionally, FIR filters can provide a linear phase response, allowing for the preservation of the morphological shape of the ECG signal, which is essential for precise analysis in wearable applications. While FIR filters typically require a higher order than IIR filters to achieve comparable performance levels, they offer enhanced design flexibility regarding filter characteristics. This flexibility permits fine-tuning of filter behaviour, making FIR filters ideal for applications such as baseline wander removal, noise reduction, and artifact filtering. Their capacity to maintain a consistent frequency response further enhances their suitability in scenarios where the integrity of the ECG signal is vital.

To further enhance signal quality and reduce spectral leakage during digital filtering, windowing functions are employed. When an ECG signal is multiplied by a selected window function prior to filtering, it minimizes discontinuities at the signal boundaries. Based on the choice of windowing function, several types are commonly used, including Hamming, Hanning, Rectangular, Blackmann, and Kaiser windows. The Rectangular window, being the simplest form, does not apply any tapering to the signal and effectively truncates it. While it provides the narrowest main lobe and thus the highest frequency resolution, it suffers from significant spectral leakage due to high sidelobe levels, making it less suitable for precise ECG signal analysis where noise suppression is critical. The Hamming and Hanning windows provide a good balance between main lobe width and sidelobe attenuation, making them suitable for general ECG applications. The Blackmann window offers superior leakage reduction, albeit with a wider main lobe, which may reduce frequency resolution. In contrast, the Kaiser window is highly versatile due to its adjustable parameter, allowing fine-tuning of the trade-off between main lobe width and sidelobe attenuation. This adaptability makes it particularly useful for optimizing ECG signal processing under varying conditions [82–84]. Further, is useful for optimizing the balance between frequency resolution and leakage reduction based on the specific needs of the application. Using these windowing techniques helps improve the precision of ECG signal analysis, allowing for better interpretation of morphological features like QRS complexes, P-waves, and T-waves, thereby enhancing the precision and reliability of cardiac monitoring systems.

In conclusion, IIR filters are preferred in scenarios requiring sharp roll-offs and lower resource utilization, while FIR filters are preferred for their stability and linear phase characteristics in wearable ECG monitoring. For wearable ECG, the selection between IIR and FIR filters ultimately depends on factors such as computational efficiency, desired frequency response, and the necessity of preserving the morphological features for accurate analysis.

Adaptive Filters

Adaptive filters [82, 84] are widely utilized in wearable ECG monitoring systems due to their ability to adjust filter parameters in real time based on the characteristics of the input signal, thereby enhancing signal quality. Unlike fixed filters, which have constant coefficients, adaptive filters can automatically modify their filter coefficients in real-time to minimize the difference between the desired output and the actual ECG signal. They employ adaptive algorithms such as Least Mean Squares (LMS) and Recursive Least Squares (RLS), to update these coefficients iteratively. However, the implementation of adaptive filters is often associated with increased computational complexity and higher power consumption, which can limit their suitability for resource-constrained wearable devices. To address these limitations, model-based adaptive filtering techniques such as the Kalman filter are employed. The Kalman filter provides optimal state estimation for linear systems under Gaussian noise conditions by recursively predicting and updating system states, offering improved computational efficiency. In contrast, for nonlinear and non-Gaussian environments, Monte Carlo-based particle filters are preferred. These filters provide greater flexibility and robustness in handling complex signal dynamics but incur significantly higher computational cost. Thus, while particle filters offer enhanced adaptability, the Kalman filter remains a more computationally efficient solution, albeit constrained by its underlying assumptions of linearity and Gaussian noise.

Furthermore, the integration of advanced signal processing techniques with artificial intelligence, including machine learning and deep learning, enhances pattern recognition and feature extraction. This leads to improved decision-making and more accurate cardiac insights in wearable applications.

2.5 Conclusion

The development of wearable ECG monitoring systems is greatly influenced by advancements in signal processing, which are crucial for ensuring high signal quality through effective noise reduction for real-time and continuous cardiac monitoring. Key design considerations for wearable ECG devices include the compatibility of the AFE with the wearable transducing medium, power consumption, battery life, and miniaturization. Among these factors, the AFE compatibility is particularly important, as dynamic variations in skin–electrode contact impedance can substantially degrade signal quality. Thus, maintaining stable skin–electrode interfacing, often resulting in high contact impedance exceeding 10 MΩ, necessitates the design of robust amplification systems and the integration of advanced signal processing methods to ensure reliable biopotential acquisition, regardless of the transducing medium used.

This chapter systematically highlights the key challenges and design requirements for wearable ECG monitoring devices, focusing on strategies for improving signal quality and implementing noise reduction techniques. The discussion encompasses both analog and digital filtering techniques essential for ECG signal processing. Analog signal processing involves filtering methods like low-pass, notch, and high-pass filters, which are crucial for eliminating baseline drift, powerline interference, and high-frequency noise. Additionally, digital approaches, including adaptive filtering and advanced noise removal techniques, enable improved suppression of motion artifacts and wireless interference.

Overall, this chapter provides a comprehensive overview of the current state and future directions for bio-amplifiers in wearable ECG monitoring from a circuit design perspective. It offers insights into overcoming existing challenges and enhancing the performance of ECG amplifiers, paving the way for more reliable and accurate wearable cardiac monitoring solutions.

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Chapter 3
Blockchain for Medical Data Security with Wearable Technology: A Review of Techniques, Trends, and Future Directions

Richa Pandey, Sushil Kumar Singh, Mahesh Manchanda, and Nicu Bizon

Abstract Blockchain technology has shown great promise in resolving security, privacy, and data integrity concerns. Disturbances in the domains of biomedical and clinical research over the past century have resulted in notable changes in healthcare statistics control systems. This results in progress in scientific statistics security. This is the main cause of conflict in the medical sector. Blockchain's capacity to preserve an incorruptible, distributed, clear log of all affected person statistics makes it a generation-rich for use in protective technologies. New possibilities and income sources for businesses and organisations have come from the Internet and other related technology advancements. Still, they open new opportunities for cyberattacks. Cyberattacks have recently become more focused on pilfering priceless data, including intellectual property, personal information, medical records, and financial data. This survey paper presents a comprehensive review of current advancements in blockchain-based models for safe patient data handling. It investigates different blockchain platforms, concentrating on permissioned systems like Hyperledger Fabric, and looks at how well they work in medical settings. The paper also emphasises how artificial intelligence methods, such as anomaly detection and federated learning, can be integrated to improve these systems' scalability and real-time threat detection capabilities. Maintaining strong data privacy and security requirements, wearable technology combined with blockchain offers new possibilities for real-time health monitoring. This paper also underlines how distributed platforms and wearables could enhance remote diagnostics and tailored healthcare delivery. This survey identifies important issues, research gaps, and future directions for

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creating more reliable and privacy-preserving medical data management solutions by examining current approaches, architectures, and use cases.

Keywords Blockchain · Hyperledger fabric · Consensus · Ethereum · Smart cities · Next-generation

3.1 Introduction

The healthcare industry is anticipated to undergo significant transformations with the help of blockchain technology. Healthcare asset management presents obstacles related to utilizing advanced analytics, handling unstructured data from various sources, ensuring system interoperability, and enhancing the accessibility of medical records. In healthcare, critical assets are extensively used and must be available precisely when and where needed. This necessitates continuous real-time monitoring of asset locations and predictive maintenance to ensure their functionality. The collected data can be consolidated and analysed to derive meaningful insights regarding both processes and assets. Protecting asset information is crucial for maintaining privacy and preventing tampering. The traditional method for storing medical data was more prone to attacks, which can be manual or cyber. Earlier medical reports were stored in the form of files and registers or in a computer, which was a single point of storage that can be easily modified, deleted, or stolen for various unethical motives.

The blockchain technology played an important role in securing medical data, as with the help of its decentralized nature, the data is not stored in one place, and even if someone wants to tamper data in any form, it is traceable because of the immutable ledger. Various cryptographic techniques, like encryption and hashing it safeguard patient information. Smart Contracts are also implemented to automate access control policies that ensure that data is only accessed by the authorized parties. Blockchain technology might turn the healthcare sector into a healthy state. Blockchain offers a fresh way to handle and save health data. Technology transforms conventional access methods and storage systems into a fresh and highly safe approach. Electronic medical records, or EHRs, have fundamentally changed patient data documentation, storage, and access in healthcare institutions. Electronic medical records (EMRs) are digital copies of the paper charts used in hospitals and clinics, including medical history, diagnosis, prescriptions, vaccination dates, allergies, lab results, and doctor's notes. By streamlining access to current and accurate patient data, EMS helps to streamline clinical workflow, cut administrative tasks, and enable departmental coordinated treatment. Using real-time alerts and decision support tools, electronic medical records (EMRs) reduce errors, eliminate test duplication, and provide quick patient data retrieval [1]. Cyberattacks, data leaks, and illegal access become much more likely as healthcare systems grow increasingly technologically connected. Usually, depending on centralised databases, conventional EMR systems may lead to single points of failure. One possible solution for

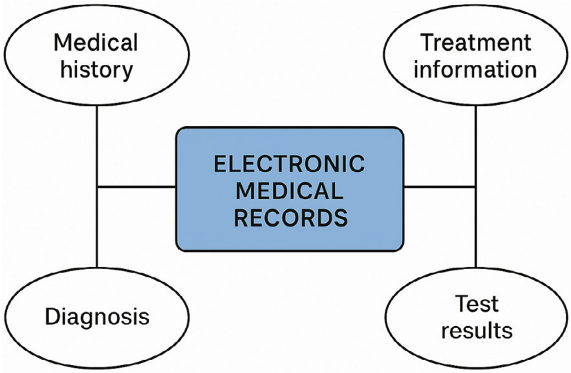

Fig. 3.1 Electronic medical report

these flaws is combining blockchain technology with electronic medical records. Blockchain distributed and unchangeable ledger guarantees improved data integrity, open audit trails, and safe access control. Better patient data security and more patient control over their medical records let this combination create a more safe and interoperable digital health ecosystem.

Along with the evolution of electronic medical records, wearable technology is becoming ever more significant in modern healthcare. Devices ranging from smartwatches, ECG monitors, to fitness trackers constantly generate biometric data that offers a patient's real-time health state interesting analysis. But this also carries risks related to illegal access and data breaches. Blockchain technology with its distributed and tamper-resistant architecture offers a strong framework to safely store, validate, and manage data collected from these wearable devices, so allowing patients to control access rights using smart contracts (Fig. 3.1).

3.1.1 Benefits of Using Blockchain in the Medical Field

There are many benefits of blockchain in the medical field, some of which we discuss:

- **Enhanced Security**: Cyberattacks target medical data most especially sensitive patient information. Blockchain technology presents strong encryption systems that protect data during storage and transmission, so addressing this issue. Blockchain runs on a distributed network, unlike centralised databases, which have a single point of failure, thus, it is quite resistant to illegal access, data modification, or system breaches. Consensus techniques verify every transaction or update made on the blockchain, so enhancing data security and integrity. Furthermore, the distributed character of blockchain guarantees that the data stays intact and safe all around the network, even in case one node is hacked.
- **Patient Control**: The empowerment blockchain offers to patients is among its most revolutionary features in the field of medicine. Patients of blockchain-based

medical systems keep complete ownership and control over their personal health records. Smart contracts that specify data sharing rights help them to ascertain who has access to their data and for what reason. These rights are unchangeable; thus, once set, they cannot be altered without the patient's permission. This improves not only personal privacy but also confidence in the healthcare system. Patients can monitor every access event in real-time, approve its use for research or diagnosis, and boldly manage their health data.

- **Transparency and traceability**: Increasing responsibility and confidence in medical data management depend much on the natural features of blockchain immutability and openness. Every change or transaction done with reference to patient records is permanently recorded on a tamper-proof, chronological ledger. This lets doctors and patients follow the whole medical record's history from inception through the most recent update. Patients could follow those who accessed their records, when, and for what purpose. This degree of traceability guarantees that all players, including labs, doctors, and insurance companies, have their data use, so strengthening system confidence.
- **Improved Data Sharing**: Conventional medical data exchange systems are prone to human error, time-consuming, and sometimes scattered nature. Blockchain lets approved healthcare providers and institutions, among other things, exchange seamless, safe, real-time data, so revolutionising this process. Standardised protocols and smart contracts enable data to be sent straight to the necessary parties, so improving coordination, reducing unnecessary tests, and accelerating diagnosis and treatment. Moreover, openness and blockchain security help to reduce data loss or miscommunication opportunities. Although this presents many advantages, if we are to provide more robust and private solutions for medical data management going ahead, we must also address ongoing problems, including interoperability, scalability, and regulatory compliance (Fig. 3.2).

3.1.2 Recent Attacks on Medical Data

Sensitive nature of medical data and growing reliance on digital health records have made medical data a top target for cyberattacks recently. Attacks on ransomware, phishing campaigns, and data leaks have all exploded inside healthcare firms. The growing frequency of cyberattacks in the healthcare sector highlights the instant need of sophisticated cybersecurity policies including blockchain and other technologies integration to guarantee the privacy and protection of medical data. Some current attack information on patient data is shown (Table 3.1).

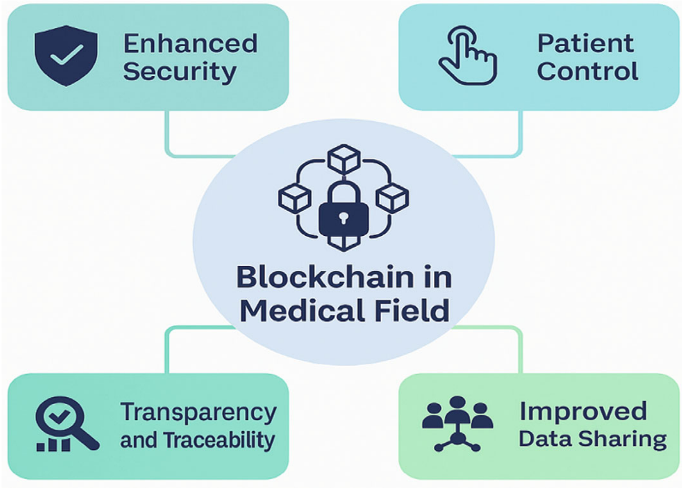

Fig. 3.2 Benefits of blockchain in medical field

Table 3.1 Recent attacks on medical data

S. no	Attack	Year	Description
1	Oracle's Cerner systems breach	March 2025	Targeting its Cerner systems, extensively used for electronic health record management, Oracle suffered a cybercrime. Involved illegal access to patient data, the hack sought to extort several U.S. medical providers. Oracle found the hack about February 20 and then informed clients in the relevant healthcare sector. It is yet unknown exactly how many compromised records there are or which particular providers were affected
2	Ambulance Victoria data breach	March 2025	An Australian emergency service called Ambulance Victoria revealed a major data hack compromising almost 3,000 staff in March 2025. Allegedly, a former employee accessed and deleted files including personal information including banking records, home addresses, and pay stubs. After learning of it, the company notified the impacted employees and locked and deleted the compromised files. Victoria Police's and Australia Federal Police's continuous investigations are ongoing

(continued)

Table 3.1 (continued)

S. no	Attack	Year	Description
3	Enzo biochem settlement	March 2025	Following a 2023 data hack revealing private patient data, Enzo Biochem, a biotechnology company, agreed to a $7.5 million settlement in March 2025. Those impacted are qualified to get two years of free credit monitoring and up to $10,000. For those affected, the hack begged questions regarding the company's cybersecurity policies and the possible hazards of fraud and identity theft
4	Holt group data breach	Jan 2025	Early 2025 saw San Antonio, Texas-based Holt Group, a machinery and construction company, disclose a data breach impacting 12,455 people. Compromised data comprised names, addresses, government-issued IDs, and financial records. Other local companies also claimed breaches, which combined affect over 16,000 Texans. Affected people have been informed; investigations are still under way

3.2 Real-Life Applications of Blockchain in Medical Science

Globally, blockchain technology is being embraced in the medical field more and more in order to guarantee patient privacy, strengthen data security, increase interoperability, and simplify healthcare processes. Blockchain-based systems have been started or adopted in many nations in fields including electronic health records (EHRs), clinical trials, drug traceability, medical billing, and health insurance. The following is a list of some noteworthy real-world blockchain projects in healthcare spanning many nations (Table 3.2).

3.3 Literature Study (Existing Works)

This section will review recent studies on the several kinds of cyberattacks aiming on medical data and healthcare systems released between 2020 and 2024. This review aims to provide a thorough knowledge of present attack routes, security flaws, and the defensive tactics suggested by academics. We hope to find current gaps in research

Table 3.2 Real-life applications of blockchain in medical Science

S. no	Country	Project	Application area	Key features
1.	Estonia	eHealth Foundation	Electronic Health Records (EHRs)	Nationwide blockchain-based solution protecting all digital prescriptions and medical records
2.	USA	MediLedger project, Hashed health	Drug supply chain, EHRs, medical billing	Guarantees drug authenticity, lowers fraud, strengthens billing and claims processing in healthcare
3.	UK	Medicalchain, guardtime	Patient-centered health records	Helps patients to securely grant access to their data; enhances cooperation in treatment
4.	UAE	Ministry of health blockchain program	Unified medical records	Blockchain integration for hospital and clinic patient record storage
5.	India	Healthereum, Tech Mahindra blockchain initiatives	Patient engagement, data sharing	Guarantees safe record sharing between providers and promotes patient involvement
6.	Canada	IBM Blockchain + Boehringer Ingelheim	Clinical trials	Increases regulatory submission integrity and openness of clinical trial data
7.	China	VeChain + DNV GL	Vaccine tracking and authentication	Blockchain-based tracking mechanism for chains of vaccination manufacture and distribution
8.	Germany	GEM Health, Iryo Network	Health Information Exchange (HIE)	Safe data flow between offices maintains patient privacy
9.	Australia	Chronicled + LinkLab	Supply chain and pharmaceutical logistics	Monitoring pharmaceutical supply chains helps to guarantee compliance and stop counterfeiting
10.	South Korea	Myongji Hospital + Bithumb	Hospital Information System (HIS)	Includes blockchain into hospital systems for safe patient record handling

and practice by means of analysis and synthesis of the results of several publications, especially in the domains of data protection, anomaly detection, real-time monitoring, and blockchain-based mitigating strategies. Furthermore, emphasised in the examined literature will be the development of threats in the medical field, the rise of AI-driven attacks, and the limits of present healthcare cybersecurity systems. The basis for suggesting a stronger and privacy-preserving solution for blockchain and artificial intelligence-based patient data security will be this assessment (Fig. 3.3 and Table 3.3).

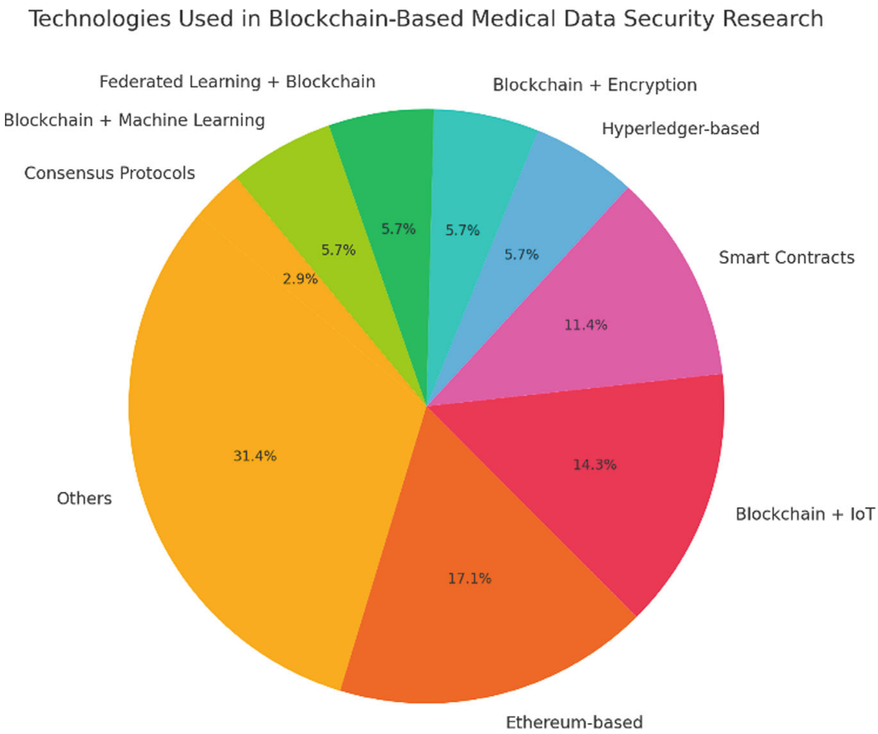

Fig. 3.3 Technologies used in blockchain research

3.4 Identification of Research Gaps

Regarding patient data security and privacy, open-ended problems are numerous. The main research gaps are:

- **Scalability**: Public blockchains often find it challenging to scale effectively, considering the massive volumes of data generated in healthcare environments. Overwhelming current blockchain systems are medical imaging, electronic health records (EHRs), and other data-intensive applications, and their high throughput and storage needs. Research is needed to create scalable blockchain solutions able to manage enormous patient data without compromising security, speed, or efficiency. These covers look at layer-2 solutions, off-chain storage techniques, and more efficient consensus systems.
- **Interoperability**: Different criteria and data structures applied by healthcare systems complicate seamless data flow. If blockchain technology is to be properly included in healthcare, it must be compatible with modern health IT systems, including EHRs, laboratory systems, and imaging tools. The main priorities of research should be the development of blockchain systems supporting universal

Table 3.3 Literature review (existing works)

S. no	Paper title	Author	Technology used	Future work
1.	Application of blockchain and IoT towards pharmaceutical industry [2]	Anitha et al. (2020)	Blockchain with IOT	• The primary challenge faced by blockchain technology is its struggle with interoperability, particularly when communication providers require thorough supply analysis to meet specific needs
2.	A systematic review of blockchain in healthcare: Frameworks, prototypes, and implementations [1]	Emeka et al. (2020)	Various blockchain technologies like Ethereum and study of architecture	• Future research should cover a thorough performance evaluation of blockchain performance applying consistent criteria based on standards
3.	Preserve security to medical evidences using blockchain technology [3]	Rupa et al. (2020)	Smart contract	• Future multi-level checks on certificate contents prior they are effectively applied on Blockchain enable singing by designated authority coming from hospitals, so enabling a multi-signature system
4.	A blockchain-based credibility scoring framework for electronic medical records [4]	Siva Rama Krishnan et al. (2020)	Ethereum platform	• Users can employ their private keys in conjunction with the interface to manage access control over their medical records, enabling them to specify who can access the records and for how long they retain a copy
5.	Artificial neural network blockchain techniques for healthcare system: focusing on the personal health records [5]	Seong-Kyu Kim et al. (2020)	Artificial neural network blockchain techniques	• It is essential to focus on the development of technologies with a more secure and well-established infrastructure • The adoption of blockchain presents the benefit of bringing fresh conveniences for industry as well as daily life

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
6.	Blockchain for COVID-19 patient health record [6]	Preethi Harris (2021)	Hyperledger Composer generator and AngularJS	• Resource planning and decision making in emergency departments during a pandemic helps one to extend their work
7.	Blockchain for secure and proper management of medical data and records [7]	Mehul Gautam et al. (2021)	EHR with Blockchain	• The complexities of the blockchain should be concealed behind a user-friendly interface, like a web or mobile application, to ensure easy accessibility
8.	Blockchain framework for secured on-demand patient health records sharing [8]	Meryem Abouali et al. (2021)	Ethereum blockchain smart contracts, the Inter-Planetary File System (IPFS)	• To assess the performance metrics of the suggested framework and explore its effectiveness in guarding against insider threats • The further plan is to expand our implementation efforts to real-time healthcare applications by accommodating a substantial increase in the number of users
9.	Blockchain traceability in healthcare: blood donation supply chain [9]	Samin Sadri et al. (2021)	Blockchain Ethereum platform	• The objective is to implement Blockchain and smart contract solutions for tracking the origins of COVID-19, a pressing issue in the present day • Additionally, it aim to harness artificial intelligence (AI) to enhance our chances of successfully tracing the source of COVID-19, as well as other epidemic diseases
10.	Blockchain-based strategy to avoid fake AI in eHealth scenarios with reinforcement learning [10]	Armando Ruggeri et al. (2021)	Smart contract, AI, reinforcement learning	• More secure and latest algorithms should be used for best results • Must have the latest attack information which are related to medical industry having Fake AI in eHealth

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
11.	CareBlocks: A blockchain-based health information sharing framework for medical IoT [11]	Sireejaa Uppal et al. (2021)	CareBlocks and IOT	• Using data kept on the IPFS (InterPlanetary File System), the authors hope to develop a machine learning model for disease prediction
12.	Illicit account detection in the ethereum blockchain using machine learning [12]	Rahmeh Fawaz Ibrahim et al. (2021)	J48, Random Forest and KNN, Ethereum blockchain	• To replicate the research study on an expanded dataset to ensure the consistency of the high accuracy rate when employing the same set of chosen features
13.	Privacy preserving computation on health care data [13]	Neha Salunke et al. (2021)	Comprehensive trustworthy data collection, WSN	• In the future, this system has the potential to be employed for secure real-time communication between healthcare professionals and patients
14.	Bibliometric analysis on blockchain technology in healthcare [14]	Sukhpal Kaur et al. (2021)	VOS Viewer, PubMed database	• The analysis shows that there is need of high level of security and privacy when it comes to patient data
15.	Security and privacy of patient information in medical systems based on blockchain technology [15]	Wu, H et al. (2021)	Elliptic curve Diffie-Hellman key exchange, MATLAB	• The practical impact of this technology in other domains should undergo further exploration • Incorporating other encryption techniques, such state encryption and proxy encryption
16.	Implementation of blockchain technology using hash method in java for medical record application development [16]	Tryan Jaya et al. (2022)	Hash algorithm, Java	• Blockchain uses strong security elements and hash to protect medical records.Every modification to records is tracked, so preserving a legacy • This guarantees open and easily traceable data management. The study invites next studies to address issues in the healthcare system
17.	ACCORD: A scalable multileader consensus protocol for healthcare blockchain [17]	Golam Dastoger Bashar et al. (2022)	ACCORD, a multi-leader (quorum-based) protocol, Consensus protocol	• It would also be interesting to investigate methods for estimating future votes without depending on the transaction list and keeping a mechanism to stop the infinite expectation of quorum membership

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
18.	Security and privacy for healthcare blockchains [18]	Rui Zhang et al. (2022)	EMRs and IOT	• Better security methods can be proposed in future for better services regarding data in healthcare blockchains
19.	Hybrid blockchain database systems: design and performance [19]	Ge et al. (2022)	Veritas and blockchain DB	• Time spent in every main component of a hybrid blockchain database system reveals that poor performance in these systems stems from consensus protocols
20.	Optimization and evaluation of authentication system using blockchain technology [20]	Imam Riadi et al. (2022)	Smart contract, SQL injection, Ethereum, metamask	• In future latest dataset can be used with all attributes for better results This research also provides a detailed exploration of the attack strategies
21.	Integrating blockchain technology into healthcare through an intelligent computing technique [21]	Asif Irshad Khan. (2022)	Fuzzy analytical hierarchy process, technique for order of preference by similarity to ideal solution	• Numerous other Multi-Criteria Decision Making (MCDM) approaches exist within the realm of technology, and their assessment through various integration methods is an area that is yet to be explored
22.	BLOSOM: Blockchain technology for security of medical records [22]	Rahul Johari et al. (2022)	BlockChain algorithm, proof of work, Merkle tree formulation, Python	• The study suggests that by expanding the dataset, it is possible to conduct a follow-up study to assess the efficacy of the research
23.	A secure healthcare 5.0 system based on blockchain technology entangled with federated learning technique [23]	Abdur Rehman et al. (2022)	Federated learning, Blockchain, IoMT, IDS	• The proposed system's computational complexity is limited as the number of secret layers rises. The studies further wish to more precisely identify and measure these influencing elements in next studies

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
24.	Secure and trustable electronic medical records sharing using blockchain [24]	Alevtina Dubovitskaya et al. (2022)	Ethereum, Hyperledger	• In the long run, the author aspire to delve into the additional scenarios outlined in the research paper, such as connected health and medical data research, and put them into practical application to enhance the current state of healthcare data management
25.	Analysis of blockchain in the healthcare sector: application and issues [25]	Ammar Odeh et al. (2022)	Electronic health records, chaincode blockchain	• This network presents its own set of challenges, including high energy consumption, limited scalability, delays in processing, traffic overhead, complexity, and relatively lower security levels
26.	Access control and privacy-preserving blockchain-based system for diseases management [26]	Kebira Azbeg et al. (2023)	Blockchain, healthcare, information and communication technology (ICT), Internet of Things (IoT), Inter Planetary file system (IPFS), proxy re-encryption	• The suggested system provides an elevated level of security when contrasted with the most advanced existing techniques • At present, authors are in the process of creating a web-based iteration of the solution • In upcoming endeavors, authors intend to introduce an intermediary "fog layer" positioned between medical devices and the hospital, with the primary purpose of screening and refining data before it is transmitted to the hospital
27.	Blockchain in healthcare data [27]	Mukesh Varman D. K. et al. (2023)	GANACHE, IPFS-INTERPLANETARY FILE SYSTEM	• Utilizing blockchain technology guarantees the integrity and openness of data, establishing a verifiable and transparent medical history record • This assures that healthcare providers have the ability to retrieve a comprehensive medical history for a patient, empowering them to make well-informed decisions regarding patient care

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
28.	BSFR-SH: Blockchain-enabled security framework against ransomware attacks for smart healthcare [28]	Mohammad Wazid et al. (2023)	Intrusion detection, machine learning, blockchain	• The future work will strive to enhance the framework's accuracy while maintaining its security integrity, ensuring that no compromise occurs in the security aspect of the scheme
29.	Significance of blockchain technology in the healthcare sector [29]	Amarnath Galaba et al. (2023)	Blockchain, Electronic Medical Records (EMR), Smart contracts	• The future growth of blockchain in the healthcare industry is highly likely. This technological advancement will drive improvements in healthcare applications by simplifying the tracking of treatment outcomes and progress
30.	Determinants of blockchain adoption and organizational performance in the healthcare sector in India [30]	Gaurav Kabra et al. (2023)	Blockchain adoption (BCA) determinants	• The model was initially designed for the healthcare sector in India, but its applicability extends to other countries with similar business environments
31.	The impact of blockchain and AI in the healthcare [31]	R. Thatikonda et al. (2024)	Hyperledger fabric, federated learning	• The study suggests further research and practical implementation in healthcare technology, emphasizing the development of scalable and compatible blockchain systems
32.	Enhancing data security and privacy through blockchain and machine learning [32]	Gurunath Machhale et al. (2024)	Blockchain and machine learning	• Authors have introduced a new framework that combines blockchain and machine learning, incorporating the necessary components • They compared this proposed framework with existing frameworks based on ACO and SVM using accuracy as the metric

(continued)

Table 3.3 (continued)

S. no	Paper title	Author	Technology used	Future work
33.	A blockchain-enabled split learning framework with a novel client selection method for collaborative learning in smart healthcare [33]	Siva Sai et al. (2024)	IOT, FL	• The future work includes a hardware implementation of the proposed framework to assess its feasibility for real-world deployment
34.	Digital privacy in healthcare: State-of-the-art and future vision [34]	Shalaka S. Mahadik et al. (2024)	Blockchain, federated learning	• The article explores the challenges associated with using AI for healthcare digital privacy and highlights recent advancements in this area • It concludes with a forward-looking perspective on the future of data privacy in healthcare
35.	Securing patient data in the healthcare industry: A blockchain-driven protocol with advanced encryption [35]	Sourav Kunal et al. (2024)	Blockchain and cryptographic algorithms	• The system creates a safe framework to guard private medical data all through the process by using blockchain technology, patient biometric information, and strong cryptographic algorithms (ECC and AES)

healthcare data standards (like HL7, FHIR) that can easily interact with legacy systems to guarantee accurate and smooth data exchange across institutions.

- **Data Privacy**: Patient data privacy remains a big problem, even if blockchain security is rather robust. Though transparency is a major advantage, it has to be balanced with the medical field's demand for privacy. Researching cutting-edge cryptographic techniques, such as homomorphic encryption, differential privacy, and zero-knowledge proofs, will enable access to data while maintaining privacy. These systems protect private patient data by allowing authorized users to access necessary data without revealing the complete dataset.
- **Regulatory Compliance**: Rules, including the General Data Protection Regulation (GDPR) in the EU and the Health Insurance Portability and Accountability Act (HIPAA) in the US, help to underline control of healthcare. Blockchain applications have to be carefully developed to follow these guidelines covering auditability, data portability, and the right to be forgotten. Blockchain designs compliant with regional and global healthcare regulations must be created through research so that the system stays transparent, safe, and functional while yet allowing compliance.
- **Consensus Mechanisms**: Every one of the several consensus algorithms, Proof of Work (PoW), Proof of Stake (PoS), and Practical Byzantine Fault Tolerance (PBFT), applied in different blockchain systems has specific effects on security and efficiency. The scalability, energy economy, capacity to maintain high data integrity, and availability of these systems define their fit in the framework of healthcare. Research is required to identify and maximize consensus models most fit for healthcare uses where fast, safe, and energy-efficient data validation is absolutely essential.
- **Smart Contracts**: Among other things, smart contracts ease data access control, consent management, and healthcare transactions. Their contribution is absolutely essential to ensure safe and clear patient data handling. Still, weaknesses in smart contract language could raise major security issues. Development of verifiable, safe, efficient smart contracts able to support complex healthcare operations and policies while reducing the risk of errors or exploitation should be the main focus of research.
- **Security Vulnerabilities**: Although blockchain security is well-known, network and application development on it still suffers from weaknesses. Attacks including endpoint vulnerabilities, smart contract exploits, and 51% attacks could compromise sensitive health data including Constant research is necessary for identification, analysis, and mitigation of these hazards; hence, blockchain resilience is strengthened, and patient data stays protected against both internal and external security breaches.
- **Cost and Energy Efficiency**: Particularly in PoW-based systems, blockchain solutions' energy consumption and running costs, as well as their deployment expenses, can be prohibitive. This raises problems about the medical field blockchain sustainability. Research should focus on developing reasonably priced, energy-efficient blockchain models, maybe by means of hybrid architectures or

lightweight consensus algorithms, so enabling the technology to be practical for real-world medical uses.

- **User Experience**: Blockchain systems in the sector have to be straightforward and easy to use for managers, doctors, and nurses equally. Complicated interfaces or too technical implementations can cause acceptance problems. Research should focus especially on the development of user-friendly platforms that easily incorporate blockchain into present procedures so that usability is not compromised for technological advancement.
- **Long-term Data Storage**: Healthcare data—especially patient records—must often be kept for decades for legal, medical, and research needs. Blockchain systems support long-term, tamper-proof data storage and must ensure that data stays accessible, safe, and whole over time. Research on hybrid storage solutions combining off-chain secure storage with on-chain verification will help to strike efficiency and lifetime.
- **Education and Adoption**: One of the hardest challenges is the encouragement of blockchain adoption among patients, healthcare providers, and institutions. Many of the involved parties either lack knowledge of any benefits of the technology or question them. Research must look for ways to teach these groups about blockchain's possibilities, dispel misconceptions, and build trust by means of awareness campaigns, pilot projects, and well-defined use cases.
- **Economic Models**: Blockchain has to be financially viable if it is to be sustainable in the medical domain. One should look at innovative and environmentally friendly economic models, including public–private alliances, subscription-based services, or token-based incentives for data sharing. These models should ensure that patient data stays safe and ethically regulated while yet enabling long-term operation and adoption.

3.5 Future Research Directions

The following research directions have been decided based on the analysis of present studies conducted within the framework of blockchain-based solutions for healthcare systems. With an eye towards scalability, interoperability, integration with new technologies, quantum resistance, legal frameworks, these directions seek to solve the problems in the current environment and suggest enhancements to present frameworks (Fig. 3.4).

- **Scalability Remedies**: Among the main challenges stopping blockchain technology acceptance in healthcare systems is scalability. Blockchain systems have a limit in transaction throughput that might lead to a bottleneck as the system expands to handle enormous amounts of healthcare data. The main future emphasis of research is on the enhancement of consensus mechanisms to reduce blockchain system running expenses without compromising their security. Currently, defining blockchain networks, including Bitcoin and Ethereum,

Fig. 3.4 Future research directions [38]

are consensus mechanisms like Proof of Work (PoW) or Proof of Stake (PoS), which can be resource-intensive and result in high running expenses. Research into alternative consensus protocols, including Proof of Authority (PoA), Proof of Elapsed Time (PoET), and hybrid consensus models, could perhaps provide more affordable and energy-efficient solutions for healthcare blockchain systems. These systems would have to balance ensuring that decentralising and security are not sacrificed with cutting energy consumption. Future research of lightweight consensus algorithms that can maintain the integrity of healthcare data, with minimum overhead costs, undermined by corruption, will help to scale blockchain solutions in the healthcare sector.

- **Interoperability Over Systems**: Blockchain systems used in labs, hospitals, and other healthcare facilities have to be flawless across several platforms and businesses. Effective blockchain acceptance in healthcare is mostly hampered by a lack of system interoperability. If we are to solve this issue, future research should focus on developing protocols and standards allowing cross-platform interoperability. These protocols would enable safe and efficient data exchange between several healthcare systems. Moreover, under investigation could be interoperability standards and cross-chain communication, so that healthcare data could move between several blockchain systems. Blockchain in healthcare would become more scalable and flexible if different businesses and entities could exchange data on a shared platform free of compatibility issues. Future studies in this area could also look at how blockchain, combined with other distributed technologies, including Distributed Ledger Technology (DLT), might create a more robust and efficient system for healthcare data exchange. By means of frameworks, researchers can lay the foundation for standardising data formats, encryption, and communication channels, thereby creating a more linked healthcare ecosystem.

- **Interaction with New Technologies**: The combined development of technologies blockchain and other technologies offer great chances to enhance healthcare systems. One interesting direction is provided by blockchain combined with federated learning. Federated learning allows data sharing-free training of machine learning models over scattered data sources. In the healthcare industry, this approach could enable patient record privacy-preserving machine learning. Combining blockchain's immutable record-keeping capabilities with federated learning will allow healthcare companies to guarantee that patient data stays safe and so use advanced analytics for decision-making still ensuring security [36]. Another just-emerging technology that might improve blockchain-based healthcare systems is edge computing. Edge computing allows data processing of medical devices or wearables almost at the source of generation. By spreading some of the computational activities to edge devices, healthcare systems can reduce latency and improve real-time performance in applications including patient monitoring, diagnostic tools, and telemedicine. Furthermore, the combination of Explainable Artificial Intelligence (XAI) and blockchain might improve the openness of medical decision-making. XAI seeks to give human-understandable justifications for AI model predictions so enabling doctors to rely on advice motivated by artificial intelligence. Including XAI into blockchain-based systems ensures that artificial intelligence decisions are not only accurate but also reasonable, so enhancing clinical acceptance and patient safety.
- **Blockchain Security Sensible Quantum Resistance**: Fast development of quantum computing makes future-proof blockchain systems against possible hazards by quantum algorithms more indispensable. Blockchain security is developed depending on current cryptographic methods, including RSA and elliptic curve cryptography, which quantum computers could be able to destroy. Future studies should concentrate on looking for post-quantum cryptographic solutions to solve this problem so that blockchain systems stay safe in the age of quantum computing. The development of cryptographic techniques free from quantum computer attack capability is known as post-quantum cryptography (PQC). Research in this field could concentrate on developing PQC-based consensus systems, digital signatures fit for blockchain systems applied in the healthcare sector, data encryption techniques, and long-term adoption and dependability

in important sectors, like healthcare, and dependability on blockchain networks being able to resist the threats of quantum computing.

- **Legal and Regulatory Framework**: Using blockchain technologies in healthcare is surrounded by a legal and regulatory environment still complicated and particular depending on the country. Blockchain systems have to follow many rules and laws, including the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States. Future studies should look at how these laws affect blockchain acceptance and suggest blockchain designs guaranteeing compliance with privacy and data protection criteria. Blockchain involvement in patient consent and data ownership is one of the key topics of research in this discipline. The distributed character of blockchain could enable patients to be more in control of their medical records. New models and rules will be needed, nevertheless, to guarantee that this control fits legal systems, including those regulating consent and data access. Research could concentrate on designing blockchain systems compliant with laws for healthcare that solve these issues and guarantee the safe and private patient data exchange.

Moreover, research on the integration of blockchain with modern legal systems and healthcare policies could help to close the gap between creativity and control. This would ensure that blockchain technologies are embraced without violating ethical standards or present laws, so promoting general acceptance in the healthcare industry.

3.6 Case Study (Applied Blockchain and Federated Learning Improves Healthcare Data Security)

Consider a hypothetical situation a system of hospitals, clinics, and diagnostic labs under "MedSecure Health Network," a sizable healthcare company manages patient data across many departments and sites. Recently MedSecure Health Network has seen an increase in cyberattacks targeted at private patient data. Mostly phishing and ransomware, these attacks have caused data loss and disruptions to healthcare systems. Given the rise in cyberthreats, the company searches for a whole solution that guarantees data privacy, enhances security, and allows patient information to be safely shared across distributed platforms. To address this problem MedSecure Health Network decides to incorporate blockchain and federated learning into its system. Blockchain provides tamper-proof, unchangeable storage for patient records while federated learning will enable decentralised and privacy-preserving machine learning on patient data.

3.6.1 Solution Review

Blockchain and federated learning combined will guarantee the safe storage, processing, and sharing of medical data all around the company. While federated learning guarantees that the sensitive patient data never leaves its original location, so preserving privacy while allowing machine learning for analytics, blockchain guarantees data integrity and transparency. Medical data will be kept and managed using blockchain technology, so guaranteeing that patient records are secure, tamper-proof, and accessible just by authorised users. MedSecure Health Network guarantees that only trusted entities (such as labs, hospitals, clinics) can access and update patient records by using a permissioned blockchain. Federated Learning for Decentralised Machine Learning will be used to train machine learning models devoid of patient data sharing amongst institutions. Every healthcare organization hospital, clinic, lab will train a local model using its own data rather than forwarding unprocessed data to a central server. Shared and aggregated in a distributed, safe manner only are model updates not raw data. This lets the system preserve patient privacy while using big data to train machine learning models.

3.6.2 System Architecture

- **First: Medical Record Storage Based on Blockchain**: Register of Patients: Every MedSecure Health Network facility adds the basic information name, date of birth, medical history of every new patient they visit to the blockchain ledger as a hash, so guaranteeing immutability. Every time a patient has a fresh test or receives treatment, the medical data such as lab findings, prescriptions, diagnosis is safely added to the blockchain on the blockchain. Over several nodes in the permissioned blockchain network, this data is cryptographically hashed and stored. Based on role-based access, only authorised medical staff members may view the data. Smart contracts guarantee a clear audit trail by enforcing access rules and automatically recording all data exchanges.
- **Second: Medical Data Federated Learning for Machine Learning**: Every hospital or clinic part of the MedSecure Health Network can teach a local machine learning model on its own data. Using past data, a local model might, for instance, forecast patient outcomes or spot possible diseases. Each facility shares simply the model updates that is, the learnt parameters, gradients, or weights with a central aggregator instead of raw patient data, so ensuring that sensitive data never leaves the premises. The central aggregator who might be a secure federated learning server gathers all the model updates from many healthcare organisations, compiles them, and produces a better global model.
- **Global Model Distribution**: Each healthcare institution receives the aggregated model back-dated for additional training. This iterative process keeps enhancing

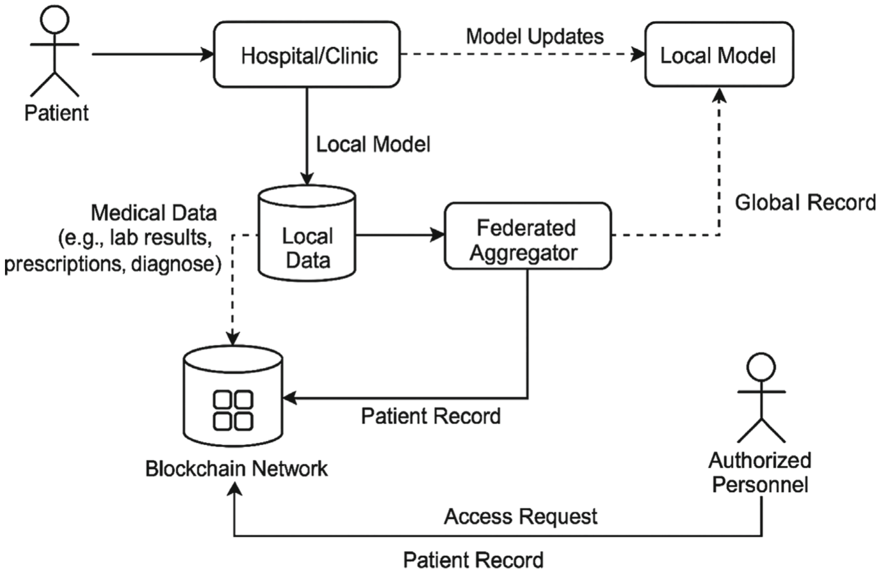

Fig. 3.5 Case study-based diagram

the model throughout time. Below is the diagram showing the case study in an expanded way (Fig. 3.5).

3.6.3 Advantages of the Suggested Solution

Blockchain's distributed character and cryptographic algorithms guarantee that medical records are safe from manipulation, so preserving high degrees of data integrity and privacy. While it still allows strong machine learning analytics, federated learning ensures that sensitive patient data is never shared with a central server, greatly reducing the risk of data breaches [36]. For present healthcare systems, blockchain and federated learning taken together provide a scalable solution with basic integration capability. This maintains data privacy and lets many labs, clinics, and hospitals operate safely together. The open and unchangeable ledger of blockchain guarantees an auditable trail of all interactions with medical data, ensuring compliance with healthcare rules, including HIPAA and GDPR. Blockchain and federated learning allow MedSecure Health Network to create a strong, scalable, and privacy-preserving system to protect private medical data, enabling advanced analytics. Since it addresses security concerns and the demand for distributed data processing, modern healthcare companies handling increasing cyber risks would find this hybrid approach ideal.

3.7 Discussion and Limitations

3.7.1 Discussion

This review makes clear that blockchain not only solves many of the urgent problems related to conventional electronic health record (EHR) systems but also enhances trust and traceability inside healthcare processes. By including decentralisation, immutability, transparency, and fine-grained access control, blockchain technologies integration into medical data security has great potential to change healthcare systems. Blockchain ensures that once data is written it cannot be altered, thus it uses consensus mechanisms and cryptographic hash to greatly reduce the risk of fraud and illegal changes. Using permissioned blockchain systems like Hyperledger Fabric better suited for healthcare because of their great throughput, access control, and privacy-preserving mechanisms, marks notable advancement. Among other legal requirements, these systems can be tailored to fit HIPAA and GDPR. By means of integration with federated learning and artificial intelligence-based anomaly detection, it also provides a real-time means of protection against both internal abuse and outside cyber threats against private patient information. The synergy among these technologies creates a stronger and more scalable framework for analytics and safe medical data flow. Support of smart contracts by blockchain also generates fresh concepts for patient-centric healthcare. Patients have more influence over whose views of their data and under what circumstances. Blockchain also offers the means for multi-institutional data exchange without compromising privacy, so opening the road for major group medical research [39, 40]. Even if their overall acceptance is still in early stages, systems including MedRec, OmniPHR, and Guardtime show real-world viability.

Still, blockchain is not a magic bullet solution for all problems. Moreover, complicating the technical, legal, and social elements of blockchain deployment in healthcare is their real use. Still demanding of us are scalability, latency, data storage, and interoperability. Lack of technical knowledge and confidence in rather new systems results in slow user acceptance among hospitals and professionals. Mostly closing this divide will depend on education, incentives, and supporting policies, as well as on. Still another hotly debated topic is the moral and legal implications of blockchain use in the medical field. Although blockchain guarantees data transparency, it may also cause questions on patient anonymity and data re-identification. Particularly in highly controlled industries like healthcare, finding a balance between openness and privacy is quite crucial. Different national data security policies complicate cross-border data flow on a worldwide blockchain network. Modern research and application direction, as well as the obstacles, point to increasing curiosity in blockchain-based healthcare systems. To build smart, responsive, and safe healthcare ecosystems, future systems will most certainly combine blockchain, IoT, edge computing, and distributed artificial intelligence models.

Emerging as a transforming tool in contemporary healthcare, wearable technology lets patients monitor their continuous data collecting in real-time. Many health data heart rate, blood pressure, glucose levels, oxygen saturation, even mental health indicators are produced by smartwatches, fitness trackers, ECG monitors, and biosensors. Even if they offer great opportunities for proactive healthcare and management of chronic diseases, these data sources generate major issues about data privacy, security, and integrity. Combining wearable technology with blockchain technology is one creative response to these challenges. Blockchain can be used as a distributed, tamper-proof ledger to store and validate wearable-generated health data, so ensuring that the data remains safe and just accessible to authorised users. Moreover, smart contracts can automatically provide data-sharing rights, so enabling patients to control who access their real-time medical records [41].

3.7.2 Limitations

Blockchain technology presents great benefits, but several constraints prevent its general implementation in healthcare environments:

- **Storage restrictions and scalability**: Their capacity to scale is intrinsically limited on blockchains. While private blockchains, though faster, still have storage constraints, public blockchains like Ethereum suffer from low transaction throughput. Large in volume and inappropriate for direct on-chain storage are medical records, including imaging and genomic sequences. This calls for hybrid designs whereby actual data resides off-chain and only metadata or hash pointers are kept on-chain, so adding system complexity and trust dependencies on outside storage systems.
- **High Implementation Charges**: Blockchain-based healthcare infrastructure first setup and maintenance call for a large financial outlay. Node configuration, staff training, system integration, smart contract development, and legal compliance, all of which have expenses. Small to mid-sized healthcare providers may find these costs prohibitive, which would restrict the acceptance of blockchain-based systems.
- **Public Blockchains' Energy Consumption**: Proof of Work (PoW) consensus systems eat enormous energy. While more recent systems like Hyperledger rely on energy-efficient alternatives (e.g., PBFT, RAFT), many systems still depend on PoW-based infrastructures. In healthcare, which stresses cost-effective sustainability, this creates a practical restriction [38].
- **Standardising and Interoperability Problems**: Current healthcare data systems follow heterogeneous criteria (e.g., HL7, FHIR, DICOM) and are scattered. One of the main difficulties is reaching flawless interoperability between these protocols and blockchain systems. Systems find it challenging to connect since there are still no generally accepted protocols for blockchain-enabled health data exchange.
- **Legal and Regulatory Obstacles**: Blockchain systems might not quite fit current health data privacy regulations. Under the GDPR, for instance, users have the

"right to be forgotten," which runs counter to blockchain immutability. For healthcare companies using blockchain technologies, this creates legal uncertainty and possible non-compliance hazards.

- **Technical awareness and User Adoption**: Healthcare professionals have little technical understanding of blockchain's possibilities, implementation, or ramifications. Blockchain technologies' slow acceptance in the medical field is a result of resistance to change, inadequate training, and anxiety of operational disturbance.
- **Integration Point Security Vulnerabilities**: Though systems interacting with the blockchain, such web portals, mobile apps, IoT devices, could have flaws even if the blockchain itself could be safe. Should these points lack sufficient security, attackers could use them to access data illegally or modify smart contracts.
- **Ethics Issues**: Blockchain openness and traceability, especially in sensitive medical environments like mental health or sexual health records, raises moral issues about loss of anonymity and surveillance. Furthermore, artificial intelligence models included in blockchain systems could have opaque decisions or inherit prejudices, so compromising patients should improper control be neglected. These constraints allow many present challenges to be solved by continuous blockchain technology developments—Layer-2 solutions, privacy-preserving cryptography (e.g., zero-knowledge proofs), and federated learning integration. Supported by policy changes and stakeholder education, a strategic and phased approach to blockchain adoption can help to realise a secure, distributed, patient-centric healthcare data ecosystem.

3.8 Future Work: Towards Scalable, Interoperable, and Secure Blockchain-Enabled Healthcare Systems

Future research must go beyond conceptual prototypes to develop and implement totally scalable, interoperable, and regulatory-compliant blockchain systems as the healthcare sector keeps changing with the integration of emerging technologies. Although the examined work has underlined the advantages of blockchain and federated learning for data privacy and integrity, many opportunities and difficulties still need to be addressed if we are to realise a truly patient-centric and safe ecosystem.

3.8.1 Modern Scalability and Energy-Efficient Consensus Systems

Overcoming limits on the scalability of present blockchain systems is a main focus of research. Real-time monitoring records, diagnostic images, and genomic datasets, among other high-throughput data sources the healthcare industry generates. Next projects should centre on:

- While preserving on-chain integrity, apply Layer-2 scaling techniques, including roll-ups or state channels to control off-chain data interactions.
- designing and benchmarking lightweight, healthcare-specific consensus algorithms (e.g., Proof of Authority, DAG-based protocols) that lower latency and energy use while maintaining data authenticity.
- Investigating sharding or multi-chain designs for parallel patient record and medical transaction processing across several departments of a hospital.

3.8.2 Blockchain Integration and Federated Learning for Instant Decision Support

Blockchain and federated learning (FL) together offer a transforming model for healthcare analytics. The aim of future systems should be:

- Using FL, enable distributed, real-time training of AI models on patient data while preserving blockchain-logged model updates' transparency.
- By means of smart contracts defining data access policies, model aggregation logic, and responsibility mechanisms, we guarantee strong security and trust.
- Using blockchain nodes at healthcare edge devices, extend this hybrid model for predictive diagnostics, customised medicine, and early outbreak detection.

3.8.3 Blockchain Interoperability with Legacy EHR Systems and IoMT Devices

Future blockchain architecture has to become fundamentally based on interoperability if we are to enable flawless communication between several healthcare institutions. Research must:

- Create blockchain middleware interacting with HL7 FHIR, DICOM, and IHE, among other generally accepted health data standards.
- Using interoperability technologies (e.g., Polkadot, Cosmos), enables cross-chain interoperability to enable patient data exchange between many blockchain ecosystems.
- Standardise blockchain integration for remote patient monitoring systems and Internet of Medical Things (IoMT) devices so as to guarantee lightweight data signing and transmission.

3.8.4 Post-quantum Blockchain Model and Quantum-Resistant Cryptographic Primitives

Blockchain's future in healthcare has to be quantum-resistant, given the explosive development in quantum computing. Investigatory areas include:

- Designing lattice-based or multivariate Poisson schemes, or post-quantum cryptography (PQC), algorithms, to guard blockchain transactions.
- Building consensus systems catered for sensitive patient data environments and quantum-safe digital signatures.
- Assessing whether hybrid classical–quantum blockchains are feasible and performable for major medical systems.

3.8.5 Policy, Ethics, and Legal Framework Integration

Policy harmonisation and ethical frameworks will be crucial to guarantee legal adoption even if the technology keeps changing. Interdisciplinary research going forward should:

- Through creative data access techniques like selective disclosure and privacy-preserving smart contracts, propose GDPR/HIPAA-compliant blockchain systems that support patient rights, including "the right to be forgotten."
- Analyse how blockchain openness affects sensitive data domains (such as sexual health, genetic disorders) and suggest protections to guarantee anonymity and permission.
- Work with legal academics to create blockchain healthcare governance models, including auditability, data stewardship, and dispute resolution systems.

3.8.6 Future Integration of Wearable Technology with Blockchain Systems

An additional essential focus of research is the integration of wearable health technologies with blockchain systems to enable distributed, real-time, safe, and secure health monitoring.

- Future systems should probe edge computing to preprocess data before blockchain commitment and look at lightweight consensus protocols fit for devices with limited resources, such wearables. Developed should be smart contract-based consent systems, federated analytics, and safe off-chain solutions to control wearable data streams in line with privacy laws.
- This orientation would find application in scalable, continuous, patient-driven digital healthcare ecosystems as well as in others [42, 43].

3.9 Conclusions

Blockchain technologies included in healthcare could drastically change patient data security, access, and storage. Blockchain solves many of the inherent constraints of conventional healthcare data systems by applying its distributed architecture, immutability, and cryptographic ideas. Particularly with relation to data integrity, privacy, and patient autonomy, these constraints have long hampered efficient management of sensitive medical information. By ensuring that patient records are tamper-proof, accessible only to authorised staff, and easily traceable for auditing needs, blockchain's open and safe character offers a new answer to these problems. With especially focus on access control, data sharing, privacy preservation, and integration with emerging technologies such federated learning and artificial intelligence, this survey has underlined the several uses of blockchain in medical data management. Blockchain guarantees patient privacy and lets medical data be securely shared between several platforms by means of distributed systems. Federated learning, for instance, lets privacy-preserving machine learning in which the models are trained locally on patient data and only the learnt parameters are shared, so ensuring that sensitive data never leaves the original site. Likewise, by giving openness and responsibility in AI-driven medical predictions, the possible integration with artificial intelligence strengthens decision-making capacity even more. Blockchain technology in healthcare is still in its early years even if it offers great benefits. Among the still difficult issues are scalability, interoperability, regulatory compliance, and getting general acceptance. The technical challenges resulting from blockchain integration with present healthcare systems guarantee that massive volumes of patient data can be controlled in real time without compromising the security or performance of the current systems. Among other healthcare laws, HIPAA and GDPR compliance remain major challenges as well as interoperability between several healthcare systems. Furthermore, the actual acceptance of blockchain technology in healthcare will call for a change of viewpoint from legislators, patients, and healthcare providers which could take time. Encouragement of constant multidisciplinary research and cooperation among technologists, healthcare professionals, and authorities will help to fully realise the possibilities of blockchain in industry. Such cooperation will be very important in developing frameworks and policies that manage the technical, legal, and ethical questions of blockchain acceptance in healthcare. As technology ages, future developments most likely will enable more ethical, responsible, scalable blockchain implementations all around the global healthcare infrastructure. These developments will pave the way for a transparent, patient-centric, safer healthcare ecosystem able to significantly raise patient outcomes, data privacy, and patient-provider confidence building.

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Chapter 4
The Intersection of Privacy, Security, and Ethics: An Empowered Framework in Wearable Technology Development

Qurat-ul-ain Mastoi and Abdullah Lakhan

Abstract This paper presents a mathematical framework for analyzing and optimizing the workloads in wearable technology systems used in healthcare, focusing on patient data processing, hospital communications, wireless networks, and user nodes. The framework incorporates privacy, security, and ethical considerations to ensure the system's integrity and fairness. The system consists of four main components: Patient Data (PD), Hospital Nodes (HN), Wireless Nodes (WN), and User Nodes (UN). Each component's workload is modeled using arrival rates and relevant parameters, such as data size, processing power, transmission bandwidth, and user resources. The total workload of the system is expressed as the sum of the individual workloads across these components. To ensure the privacy and security of patient data, the model introduces constraints on privacy and security levels, while ethical considerations are incorporated through fairness metrics. This approach provides a comprehensive methodology for balancing system performance with privacy, security, and ethical considerations, contributing to the development of reliable and trustworthy wearable healthcare technologies. The proposed methodology outlines the creation of an Ethical Privacy and Security Detection System (EPDS), which is composed of various components to handle privacy, security, and ethical fairness throughout the system. Key steps include: The system's total workload is calculated by aggregating the workloads from four main components: Patient Data (PD): Data generation rate from wearable devices. Hospital Nodes (HN): Data processing and storage requirements. Wireless Nodes (WN): Data transmission rate across wireless infrastructure. User Nodes (UN): Data access and feedback interactions. Each workload component is defined as a function of various factors, such as data arrival rates and resource demands at each node (e.g., processing power at hospital nodes, bandwidth at wireless nodes, and feedback mechanisms at user nodes). These functions

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ensure that the system operates under balanced conditions. The model integrates privacy and security constraints into the framework, ensuring that the system meets predefined thresholds for privacy (denoted as $\mathcal{P}(D)$) and security (denoted as $\mathcal{S}(D)$) to protect sensitive patient data. Ethical fairness is addressed by ensuring equitable access and minimizing biases in data handling. A fairness metric $\mathcal{E}(D)$ is defined to monitor and enforce ethical standards throughout the system. The framework allows for the optimization of workloads across nodes to balance performance and resource utilization while meeting the constraints for privacy, security, and fairness. By combining these components into an integrated framework, the study proposes a reliable approach for managing workloads in wearable healthcare technology while considering the ethical implications and ensuring privacy and security of patient data.

Keywords Privacy · Security · Ethical issues · Wearable devices · Technology

4.1 Introduction

Wearable technology, which includes devices like fitness trackers, smartwatches, and health-monitoring devices, has become an integral part of modern life. These devices offer convenience, real-time data collection, and continuous connectivity. They are often designed to monitor various health metrics such as heart rate, sleep patterns, and physical activity, providing users with valuable insights into their well-being. Furthermore, wearable technologies are increasingly being integrated with advanced capabilities such as artificial intelligence, machine learning, and cloud computing, which promise to revolutionize healthcare and other fields. However, as these technologies become more sophisticated, they raise critical concerns related to privacy, security, and ethics. These concerns are especially pertinent as wearable technologies often collect and store sensitive personal data.

The intersection of privacy, security, and ethics in wearable technology development has become an urgent area of research and discourse. Privacy concerns arise from the collection of vast amounts of personal data, often without users fully understanding how their data will be used or shared. Security risks are also prominent, as wearable devices are vulnerable to hacking, data breaches, and unauthorized access. Lastly, ethical issues arise in areas such as informed consent, data ownership, and the potential for exploitation of personal health information. As the adoption of wearable technology continues to grow, addressing these concerns is essential to ensuring that users' rights are protected and that the benefits of these technologies are maximized in a responsible and ethical manner.

Wearable technology encompasses a broad range of devices that are worn on the body, designed to collect data and provide real-time insights. These devices can be categorized into various types, including fitness trackers, smartwatches, smart clothing, and medical devices. Over the past decade, there has been an exponential increase in the popularity of these technologies, driven by advancements in sensor technology, miniaturization of electronic components, and improvements in wireless communication technologies. Wearables can track a variety of metrics, including physical activity, biometrics, environmental conditions, and even emotional responses, and they have applications in healthcare, fitness, entertainment, and more.

The adoption of wearable technologies in the healthcare sector, for instance, has been hailed as a transformative development. Devices like smartwatches are increasingly being used for monitoring chronic health conditions such as diabetes, cardiovascular diseases, and respiratory conditions. These devices not only help individuals manage their health but also enable healthcare providers to remotely monitor patients' conditions, improving the efficiency and accessibility of healthcare services. Furthermore, wearables are often integrated into broader digital health ecosystems, which include mobile health applications, cloud-based data storage, and telemedicine platforms.

While wearable technologies have the potential to enhance health outcomes and improve quality of life, they also pose significant challenges in terms of privacy, security, and ethics. The data collected by these devices is often sensitive in nature, including personal health information, biometric data, and even location data. The collection, storage, and transmission of this data raise concerns about user privacy and data protection. Additionally, the integration of wearable technologies with cloud computing and mobile applications introduces new vulnerabilities, which may expose users to security risks such as hacking and unauthorized access.

Ethical issues are also central to the development of wearable technologies. Informed consent is a key concern, as users must be fully aware of what data is being collected, how it is being used, and who has access to it. Furthermore, questions of data ownership and control are important, particularly when users' personal health data is stored in cloud-based systems that are often controlled by third parties. The potential for discrimination based on personal health data is another ethical issue that must be addressed, as the use of such data by insurance companies, employers, or other entities could lead to unfair treatment.

Given the importance of privacy, security, and ethics in wearable technology, several key research questions need to be explored:

1. What are the privacy risks associated with wearable technologies, and how can these risks be mitigated?
2. How can wearable devices ensure data security, particularly when data is transmitted to cloud-based systems?
3. What ethical considerations must be taken into account when designing and deploying wearable technologies?
4. How can users be better informed about the risks associated with wearable technologies, and what role does informed consent play in ensuring ethical practices?
5. What frameworks or regulations can be implemented to govern the use of personal data collected by wearable devices?
6. How can we balance the benefits of wearable technologies with the potential risks to privacy and security?
7. What role do manufacturers, developers, and policymakers play in ensuring the ethical development of wearable technologies?

These research questions are crucial for understanding how to design and implement wearable technologies in a way that protects users' privacy, ensures the security of sensitive data, and adheres to ethical standards. Addressing these questions will help ensure that wearable technologies are developed in a manner that benefits society while respecting individual rights and freedoms.

This study aims to contribute to the understanding of the intersection of privacy, security, and ethics in wearable technology development by providing an in-depth analysis of the challenges and potential solutions. The key contributions of this study are as follows:

1. **Comprehensive analysis of privacy risks**: This study will offer a detailed examination of the privacy risks associated with wearable technologies, particularly in relation to the collection and storage of personal health data. It will explore how these risks can be mitigated through the use of encryption, anonymization techniques, and other privacy-enhancing technologies.
2. **Security frameworks for wearable devices**: The study will explore various security frameworks and best practices that can be applied to wearable technologies to ensure the protection of data. It will focus on securing data during transmission and storage, as well as preventing unauthorized access to personal information.
3. **Ethical considerations in wearable technology development**: This research will examine the ethical issues surrounding wearable technologies, including the principles of informed consent, data ownership, and potential discrimination. It will propose ethical guidelines for developers, manufacturers, and policymakers to ensure that wearable technologies are designed and deployed in a responsible and ethical manner.
4. **Regulatory frameworks for wearable technologies**: The study will investigate existing legal and regulatory frameworks related to wearable technologies, such as data protection laws and health information privacy regulations. It will propose recommendations for new or enhanced regulations to govern the use of wearable devices and the collection of personal data.
5. **User awareness and education**: This research will emphasize the importance of user awareness and education in ensuring the ethical use of wearable technologies. It will explore methods for improving users' understanding of privacy and security risks, as well as their rights regarding data ownership and consent.
6. **Proposals for balanced design**: Finally, the study will propose strategies for balancing the benefits of wearable technologies with the potential risks to privacy and security. This includes recommendations for developers and policymakers on how to create systems that protect user privacy while still enabling the beneficial use of data for health and wellness purposes.

By addressing these issues, the study will contribute to the development of wearable technologies that are secure, privacy-respecting, and ethically responsible. It will provide valuable insights for developers, researchers, policymakers, and consumers, helping to guide the future of wearable technology in a way that prioritises user rights and ethical standards.

4.2 Related Work

Wearable technologies have become a focal point in discussions surrounding privacy and security. Various studies have addressed the challenges these devices present, particularly in the context of data protection. Smith and Davis (2024) discuss the privacy and security concerns specific to wearable technologies in their study on the topic [1]. Ethical considerations are also pivotal, as shown by Johnson and Miller (2023), who explore the implications of these devices on personal privacy [2].

In addition, Wilson and Brown (2025) provide a comprehensive look at the intersection of wearable tech, ethics, and security [3]. Addressing security in health monitoring systems is another critical area, with Lee and Kim (2022) presenting solutions at the International Conference on HealthTech [4].

Moreover, the development of privacy protection mechanisms is key in wearable devices, as discussed by Chen and Liu (2025), who emphasise the importance of robust security frameworks [5]. Ethical challenges regarding data collection are highlighted by Patel and Zhang (2023), exploring global perspectives on wearable data collection [6].

Recent advancements in wearable technology also include blockchain-based security solutions, such as those proposed by Wang and Zhang [7]. As these technologies evolve, balancing privacy with innovation remains a significant concern, as noted by Parker and Clark [8]. This work starts security privacy and ethical formulation (SPEF) and ethical security methodology (ESM) suggested in these studies [7, 9–11].

4.3 Proposed Framework

This paper introduces a mathematical framework for analyzing workloads in wearable technology, focusing on patient data processing and communication among hospitals, wireless networks, and user nodes. The framework incorporates privacy, security, and ethical considerations into the design and deployment of wearable systems.

Wearable technology has transformed healthcare by enabling real-time monitoring of patient data. However, these advancements bring challenges in balancing workloads across nodes while ensuring privacy, security, and ethical use of data. We propose a mathematical model to optimize these aspects across patient data, hospital systems, wireless networks, and user nodes.

The system consists of four main components:

- **Patient Data (PD)**: The data generated by wearable devices.
- **Hospital Nodes (HN)**: Servers managing and analyzing patient data.
- **Wireless Nodes (WN)**: Infrastructure for data transmission.
- **User Nodes (UN)**: Devices interacting with wearable technology.

Let the workloads for each component be represented as follows:

$$\begin{aligned} W_{PD} &: \text{Workload on patient data nodes (data generation rate).} \\ W_{HN} &: \text{Workload on hospital nodes (data processing and storage).} \\ W_{WN} &: \text{Workload on wireless nodes (data transmission rate).} \\ W_{UN} &: \text{Workload on user nodes (data access and feedback).} \end{aligned}$$

The total workload W_{Total} of the system is expressed as:

$$W_{Total} = W_{PD} + W_{HN} + W_{WN} + W_{UN}. \tag{4.1}$$

Each workload can be modelled based on specific parameters:

$$W_{PD} = \lambda_{PD} \cdot S_{PD}, \tag{4.2}$$
$$W_{HN} = \lambda_{HN} \cdot (P_{HN} + S_{HN}), \tag{4.3}$$
$$W_{WN} = \lambda_{WN} \cdot T_{WN}, \tag{4.4}$$
$$W_{UN} = \lambda_{UN} \cdot (R_{UN} + F_{UN}), \tag{4.5}$$

where:

- $\lambda_{PD}, \lambda_{HN}, \lambda_{WN}, \lambda_{UN}$: Arrival rates of data.
- S_{PD}, S_{HN}: Sizes of data at patient and hospital nodes, respectively.
- P_{HN}: Processing power required at hospital nodes.
- T_{WN}: Transmission bandwidth of wireless nodes.
- R_{UN}, F_{UN}: Resources and feedback mechanisms at user nodes.

To ensure privacy and security, we introduce constraints:

$$\mathcal{P}(D) \geq \beta, \quad \text{(Privacy Level)} \tag{4.6}$$
$$\mathcal{S}(D) \geq \gamma, \quad \text{(Security Level)} \tag{4.7}$$

where $\mathcal{P}(D)$ and $\mathcal{S}(D)$ are the privacy and security metrics of the data D, and β, γ are predefined thresholds.

Ethical considerations are enforced by ensuring equitable access and minimizing biases:

$$\mathcal{E}(D) \geq \eta, \quad \text{(Ethical Fairness)} \tag{4.8}$$

where $\mathcal{E}(D)$ represents the ethical fairness metric.

This framework provides a comprehensive approach to balancing workloads across patient data, hospital systems, wireless networks, and user nodes in wearable technology. By incorporating privacy, security, and ethical considerations, the model supports the development of robust and trustworthy healthcare solutions.

4.4 Proposed Methodology

The study proposed that ethical privacy and security detection (EPDS) consisted of different components.

Algorithm 1: EPDS: Deep Learning

Require: Data streams from PD, HN, WN, and UN; privacy threshold β, security threshold γ, and ethical threshold η.
Ensure: Optimized workload distribution.
Initialize neural network NN with parameters Θ.
Define loss function $\mathcal{L}(\Theta)$:

$$\mathcal{L}(\Theta) = \alpha \cdot \left(W_{Total} - W_{opt}\right)^2 + \beta \cdot \max(0, \beta - \mathcal{P}(D)) + \gamma \cdot \max(0, \gamma - \mathcal{S}(D)) + \eta \cdot \max(0, \eta - \mathcal{E}(D)).$$

Train NN using gradient descent to minimize $\mathcal{L}(\Theta)$.
for each iteration **do**
    Collect real-time data from PD, HN, WN, and UN.
    Predict workload distribution $\hat{W} = NN(\text{data})$.
    Adjust workloads to achieve $\hat{W}$.
    Ensure $\mathcal{P}(D) \geq \beta$, $\mathcal{S}(D) \geq \gamma$, and $\mathcal{E}(D) \geq \eta$.
end for
return Optimized workload distribution $\hat{W}$.

Require: Data streams from PD, HN, WN, and UN; privacy threshold β, security threshold γ, and ethical threshold η.
Ensure: Optimized workload distribution.

Step 1: Initialize neural network NN with parameters Θ.

In this step, a neural network model is initialized with certain parameters Θ. The network will be trained in subsequent steps to optimize workload distribution.

Step 2: Define loss function $\mathcal{L}(\Theta)$:

$$\mathcal{L}(\Theta) = \alpha \cdot \left(W_{Total} - W_{opt}\right)^2 + \beta \cdot \max(0, \beta - \mathcal{P}(D)) + \gamma \cdot \max(0, \gamma - \mathcal{S}(D)) + \eta \cdot \max(0, \eta - \mathcal{E}(D)).$$

The loss function $\mathcal{L}(\Theta)$ is defined with multiple terms:

- The first term, $\alpha \cdot \left(W_{Total} - W_{opt}\right)^2$, minimizes the difference between the total workload W_{Total} and the optimized workload W_{opt}.

- The second term, $\beta \cdot \max(0, \beta - \mathcal{P}(D))$, ensures that the privacy requirement $\mathcal{P}(D)$ is met by comparing it with the threshold β.
- The third term, $\gamma \cdot \max(0, \gamma - \mathcal{S}(D))$, ensures that the security requirement $\mathcal{S}(D)$ is met by comparing it with the threshold γ.
- The fourth term, $\eta \cdot \max(0, \eta - \mathcal{E}(D))$, ensures that the ethical requirement $\mathcal{E}(D)$ is met by comparing it with the threshold η.

Step 3: Train NN using gradient descent to minimize $\mathcal{L}(\Theta)$.
In this step, the neural network is trained using gradient descent, where the loss function $\mathcal{L}(\Theta)$ is minimized iteratively. This training will help the network learn the optimal distribution of workloads.
for each iteration **do**
  Step 4: Collect real-time data from PD, HN, WN, and UN.
  Real-time data is collected from various sources: PD (Personal Device), HN (Home Network), WN (Work Network), and UN (Urban Network). This data is essential for predicting and adjusting workload distribution.
  Step 5: Predict workload distribution $\hat{W} = NN(\text{data})$.
  The neural network, NN, uses the collected data to predict the optimal workload distribution, $\hat{W}$.
  Step 6: Adjust workloads to achieve $\hat{W}$.
  The predicted workload distribution $\hat{W}$ is used to adjust the actual workloads across the system, aligning them with the optimized distribution.
  Step 7: Ensure $\mathcal{P}(D) \geq \beta$, $\mathcal{S}(D) \geq \gamma$, and $\mathcal{E}(D) \geq \eta$.
  After adjusting the workloads, it is ensured that the privacy, security, and ethical requirements are satisfied. The privacy level $\mathcal{P}(D)$ must be greater than or equal to β, the security level $\mathcal{S}(D)$ must be greater than or equal to γ, and the ethical level $\mathcal{E}(D)$ must be greater than or equal to η.
end for
Step 8: Return Optimized workload distribution $\hat{W}$.
Once the iterations are complete, the optimized workload distribution $\hat{W}$ is returned as the final output.

4.5 Simulation Result

The following table represents the components, their associated parameters, and the formula for calculating their workload.

Component	Ari. (λ)	Data Size (S)	P	T	R + F	W
Patient Data (PD)	λ_{PD}	s_{PD}	–	–	–	$w_{PD} = \lambda_{PD}$
Hospital Nodes (HN)	λ_{HN}	s_{HN}	p_{HN}	–	–	$w_{HN} = \lambda_{HN}$
Wireless Nodes (WN)	λ_{WN}	–	–	τ_{WN}	–	$w_{WN} = \lambda_{WN}$
User Nodes (UN)	λ_{UN}	–	–	–	$R_{UN} + F_{UN}$	$w_{UN} = \lambda_{UN})$

Example Values

The following table shows the components of the system.

Component	Ari. (λ)	Data Size (S)	P	T	R + F	W
Patient Data (PD)	10 MB/s	500 MB	–	–	–	$W_{PD} = 50$
Hospital Nodes (HN)	8 MB/s	200 MB	10 GB/s	–	–	$W_{HN} = 8$
Wireless Nodes (WN)	15 MB/s	–	–	2 Gbps	–	$W_{WN} = 15$
User Nodes (UN)	5 MB/s	–	–	–	1 MB + 50	$W_{UN} = 5$

Total Workload

The total workload W_{Total} of the system is given by:

$$W_{Total} = W_{PD} + W_{HN} + W_{WN} + W_{UN}$$

Using the above values, the total workload is:

$$W_{Total} = 5000 + 1680 + 30 + 255 = 6965 \text{ units of workload}$$

Figure 4.1 shows that EPDS has higher accuracy to maintain ethical security and privacy for all workloads. Figure 4.2 shows that EPDS has higher accuracy along with the processing time to maintain ethical security and privacy for all workloads.

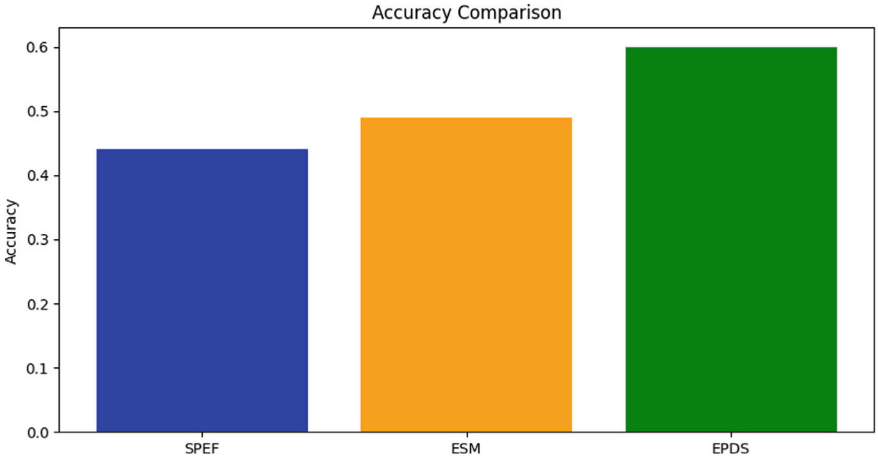

Fig. 4.1 Accuracy: Ethical, privacy, and security issues

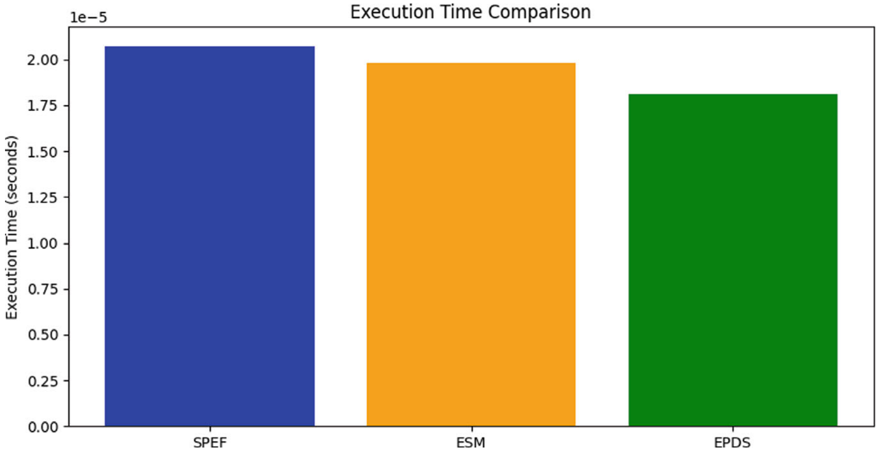

Fig. 4.2 Time: Ethical, privacy, and security issues

4.6 Conclusion and Update Work

This paper presents a comprehensive mathematical framework designed to analyze and optimize workloads in wearable healthcare technology systems. By modeling the various components–Patient Data (PD), Hospital Nodes (HN), Wireless Nodes (WN), and User Nodes (UN)–we have established a method for balancing system performance with critical considerations of privacy, security, and ethical fairness. The approach incorporates privacy and security constraints to safeguard sensitive patient data, while ethical fairness is ensured through the inclusion of fairness metrics. The proposed Ethical Privacy and Security Detection System (EPDS) offers an integrated solution to handle these complexities in real-time, ensuring that the healthcare system operates efficiently without compromising the integrity or trustworthiness of the data. The proposed framework provides a solid foundation for the design and implementation of reliable and trustworthy wearable healthcare systems. It offers valuable insights for optimizing the workloads in each node of the system while maintaining privacy and security standards. Moreover, it highlights the importance of ethical considerations in the development and deployment of healthcare technologies, providing a balanced approach to performance and fairness.

Future research could focus on further refining the workload optimization methods, particularly in the context of real-world healthcare systems. This could involve incorporating more advanced machine learning techniques for dynamic workload allocation based on real-time data analysis and system performance. Additionally, exploring the integration of emerging technologies, such as 5G networks and edge computing, could enhance the scalability and efficiency of the proposed framework. Moreover, future work could investigate the long-term impact of the ethical fairness metrics on user satisfaction and healthcare outcomes. Further empirical studies involving diverse patient populations could help to validate the fairness criteria and ensure that the system remains equitable in different healthcare settings. Investigating the robustness of the system against adversarial attacks and developing advanced security mechanisms to counter new threats will also be critical to maintaining the integrity of the system. Lastly, as wearable healthcare technologies continue to evolve, it will be essential to adapt the framework to handle increasingly complex data sources and multi-device interactions, ensuring that the system remains sustainable and effective in the face of technological advancements.

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Chapter 5
Flexible Applications of Gallium-Based Liquid Metals

Xinpeng Wang and Peng Yan

Abstract Liquid metals and their alloys have been applied in sensing technologies due to their flexibility and high electric conductivity. Especially, gallium-based liquid metals have attracted research attention because of their superior fluidity, antimicrobial capabilities, and self-healing characteristics. This chapter provides an up-to-date overview on the physicochemical properties of gallium-based liquid metals and their applications in flexible circuits and wearable sensors. Gallium-based liquid metals provide unique advantages for the development of triboelectric and piezoelectric nanogenerators, ultra-sensitive electronic skins, and electronic blood vessels. However, there are still many unknown functional forming methods and properties that deserve further exploration. The application of liquid metal in flexible areas will continue to be explored and developed, leveraging its advantages in wearable sensors.

5.1 Introduction

Liquid metals are generally characterized as metals or alloys with melting points below 300 °C, often referred to as low melting point metals [1, 2]. Mercury (Hg), a common liquid metal used in thermometers, is notorious for its volatility and toxicity, which constrains its broader application. Beyond mercury, within the 118 known elements which is shown in Fig. 5.1, the most prevalent liquid metals include Gallium (Ga), Indium (In), Tin (Sn), and so on. Notably, Rubidium, Cesium, and Francium exhibit high radioactivity, whereas Sodium and Potassium are highly reactive, presenting significant risks of combustion and explosion. In contrast, Gallium, Indium, and Tin demonstrate environmentally benign characteristics. As a result, Gallium, Indium, and other similar liquid metals have become central to scientific investigation. Notably, Gallium, with its low fusion point of 29.8 °C, exhibits exceptional fluidity and maintains the essential properties of a base metal at room

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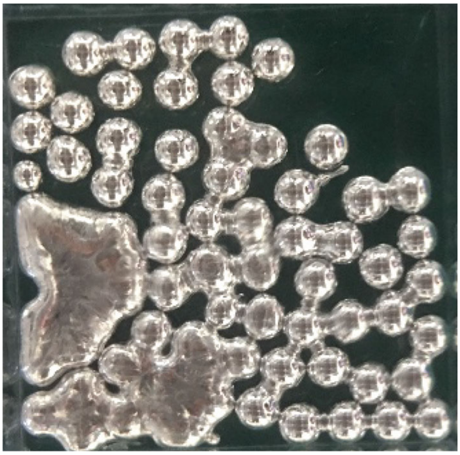

Fig. 5.1 Liquid metal (gallium) picture

temperature. These properties include high electrical conductivity, low toxicity, non-volatility, and non-radioactivity [3, 4]. In this paper, the term "liquid metal" is specifically employed to denote gallium-based liquid metals.

In recent years, gallium-based liquid metals have attracted substantial **attention** in various fields because of their desirable characteristics, which include superior fluidity, antimicrobial capabilities, and self-healing characteristics. These attributes have positioned them as promising candidates for applications in thermal management systems, biomimetic robotics, and numerous other domains [5–7].

Pure gallium is a liquid metal that is relatively widely used at present and exhibits commendable electrical conductivity in the range of 2–7 × 106 S/m, which is approximately an order of magnitude inferior to that of ordinary conductors like copper (Cu) and silver (Ag) [8, 9]. However, it typically behaves as a Newtonian fluid with a notably high surface tension of around 600 mN/m, which is ten—fold that of water [3]. Consequently, liquid metal droplets tend to be spherical and struggle to form precise shapes. Furthermore, when exposed to oxygen at the parts-per-million (PPM) level, gallium oxidizes, forming a slender oxide layer with a thickness of several nanometers [3, 10], which diminishes the surface tension of the liquid metal (LM). This surface oxide layer is able to cling to particular materials, like polyvinyl chloride (PVC), thereby promoting LM printing. Additionally, the dense surface oxide layer possesses a self-limiting characteristic, preventing the incessant oxidation of LM. Nevertheless, during mobile deformation, the original oxide layer fractures, leading to the generation of more new surface oxide, and this can somewhat impair conductivity. To enhance the performance of LM-based flexible conductors and expand their application spectrum, not only can LM alloys with varying compositions, such as GaIn, GaInSn, etc., be utilized, but also composites can be developed, including particle composites based on LM. Physical or chemical modifications of liquid metals can also be employed to apply them in a variety of material manufacturing processes, thereby advancing the utilization of flexible electronics in areas like flexible conductors [8, 9, 11, 12], printing [13, 14], architecture [15], biomedicine [16–18], etc. [19–21].

5.2 Physicochemical Properties of Gallium-Based Liquid Metals

Gallium, a fascinating liquid metal, was first identified by scholar named Boisbau Dranin in 1875 through spectroscopic method [22], but it wasn't until 1915 that it was truly refined. This silver-white liquid metal exhibits a faint silver-blue metallic sheen when it is solid and predominantly adopts an orthorhombic crystal structure [1, 23]. Once considered a metal with limited availability, gallium remained largely undeveloped for an extended period. However, over the past four decades, the relentless advancement of information technology has brought gallium into the spotlight due to its low fusion point of 29.8 °C and its distinctive metallic attributes. The primary usage of this metal is in the realms of semiconductor and photoelectric materials, petrochemicals, and medical equipment, with the semiconductor industry being the most significant consumer. Gallium is predominantly utilized in the manufacture of gallium arsenide, which are crucial constituents in semiconductors, representing approximately 80% of the overall gallium utilization [24–26]. Currently, with the ongoing growth of the IT industry, intelligent technologies, the employment of gallium metal has emerged as a subject of keen interest. The attributes of gallium are being unearthed and harnessed for an expanding array of utilizations, including medical—related uses, novel alloys, and shape memory alloys, among others. Nonetheless, there is a pressing need for more vigorous research and development of gallium in areas beyond semiconductors. As is well understood, the physical and chemical features of a material are pivotal to its subsequent study, employment, popularization. Consequently, a comprehensive grasp and mastery of the physicochemical properties of materials like gallium are not only prerequisites but also essential for enabling their optimal performance and contribution to humanity.

Owing to extensive research, the known physical properties of gallium, as depicted in Fig. 5.2, are primarily as follows:

(1) Gallium exhibits a viscosity akin to water, coupled with excellent fluidity, making it suitable for applications in actuation, thermometer [28], flexible electronics [29, 30], and biomimetic metal patterning [31] etc.
(2) It possesses good electrical conductivity, which is only an order of magnitude inferior to that of copper (3.4×10^6 S/m);
(3) Gallium's heat conductivity is commendable ($29.3\ W{\cdot}m^{-1}{\cdot}K^{-1}$), rendering it a viable material for cooling systems;

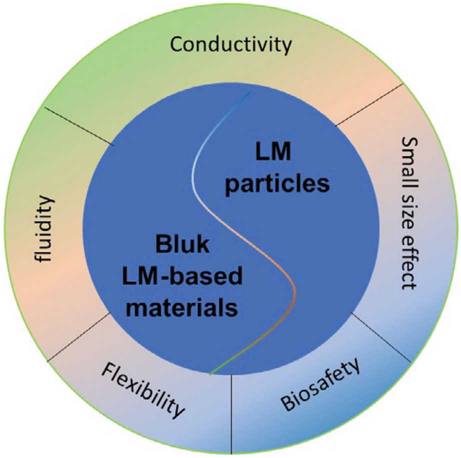

Fig. 5.2 Properties of gallium-based liquid metals [27]. Copyright by Springer

(4) The surface tension of gallium (707 mN/m) is ten times as much as the surface tension of water, facilitating the formation of steady spherical structures in its liquid state;

(5) With the fusion point of 29.8 °C and ebullition point of 2205 °C, gallium is characterized by low volatility, stability in air, ease of handling, and favorable biological safety. Additionally, it is noteworthy that gallium experiences a significant extent of supercooling between its fusion and solidification points, which means it does not solidify instantly beneath the fusion point. This property can be exploited for various liquid-based processes within this temperature range. However, if solid-state operations in the supercooled condition are desired, addressing the solidification challenge is essential.

(6) Gallium exhibits notable expansibility during its solidification process. Researchers have ingeniously harnessed this characteristic to regulate the switching behavior of insulators and conductors [32–34]. Specifically, the switch can be maintained in an off state while in liquid form, and conductivity is established through volume expansion post-solidification. The increased viscosity upon solidification can also be leveraged for bonding and gripping substances [7]. Specifically, the switch can be maintained in an off state while in liquid form, and conductivity is established through volume expansion post-solidification. The increased viscosity upon solidification can also be leveraged for bonding and gripping substances [35].

(7) Extensive research has attested to gallium's low cytotoxicity [36, 37], excellent biosafety, and radiation resistance, making it a viable material for applications in medical engineering, including those related to CT imaging [38].

On the one hand, gallium retains the chemical properties inherent to metals due to its metallic bonding. These include reactions with acids to form corresponding cationic salts, degradation; reactions with bases to form hydroxides; oxidation reactions; and substitution reactions, among others. Additionally, being a Brønsted acid among group 13 metals, gallium will automatically form Ga ions in deionized water [39]. Building on previous relevant studies [3, 39–42], the usual reactions (5.1)–(5.11) are synthesized as below.

$$Ga + H^+ \rightarrow Ga^{3+} + H_2 \tag{5.1}$$

$$Ga + OH^- \rightarrow Ga(OH)_3 \tag{5.2}$$

$$Ga(l) + O_2(g) \rightarrow Ga_2O_3(s) \tag{5.3}$$

$$Ga + H_2O \rightarrow^{ROS,\,\Delta} GaOOH \tag{5.4}$$

$$2Ga_2O_3 + H_2O \rightarrow 4GaOOH \tag{5.5}$$

$$GaOOH + H_2O \rightarrow Ga^{3+} + 3OH^- \tag{5.6}$$

$$\left[Ga(H_2O)_6\right]^{3+} + H_2O \rightarrow \left[Ga(H_2O)_5OH\right]^{2+} + H_3O^+ \tag{5.7}$$

$$\left[Ga(H_2O)_5OH\right]^{2+} + H_2O \rightarrow \left[Ga(H_2O)_4(OH)_2\right]^{+} + H_3O^+ \tag{5.8}$$

$$\left[Ga(H_2O)_4(OH)_2\right]^{+} + H_2O \rightarrow Ga(OH)_3 + H_3O^+ \tag{5.9}$$

$$Ga(OH)_3 \rightarrow GaOOH + H_2O \tag{5.10}$$

$$2Ga + 3Cu^{2+} \rightarrow 2Ga^{3+} + 3Cu \tag{5.11}$$

It is noteworthy that gallium's low ionization energy of 5.99 eV, compared to lithium at 5.39 eV and magnesium at 7.65 eV, renders it particularly appropriate for reactions involving the transfer of single electrons.

5.3 Flexible Applications

Gallium-based liquid metals possess the characteristics of both liquids and metals, with their electrical conductivity only an order of magnitude inferior to that of traditional metals like copper (approximately 3.4×10^6 S/m). Their Young's modulus is lower than that of brain tissue and muscle (as shown in Fig. 5.3), which endows them with excellent flexibility and biocompatibility. Additionally, gallium-based liquid metals can undergo solid–liquid transitions by adjusting their freezing points at

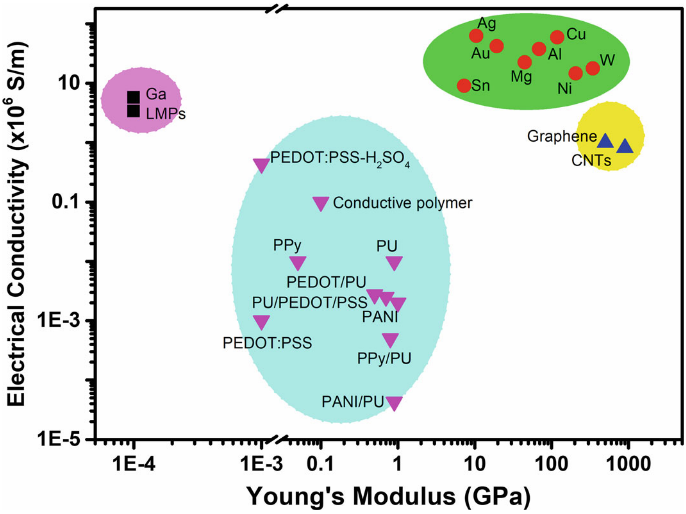

Fig. 5.3 Young's modulus of different materials [27]. Copyright by Springer

room temperature. These properties have made gallium-based liquid metal materials increasingly favored by researchers for flexible applications. From flexible physical sensing to chemical and biological sensing, from the most common stress–strain sensors, to temperature and humidity sensors, to wearable devices on the body's surface, electronic skin, to in-body sensing, from flexible electronics to biomedical engineering applications, and to the integration of flexible sensing in soft robotics, their practical application prospects are vast, and the directions for research and innovation are becoming increasingly diverse.

Firstly, as a form of epidermal sensing, dating back to 2013, as shown in Fig. 5.4, Yu et al. put forward the employment of liquid metal as stretchable ECG electrodes and skin circuits [43]. This approach opened up the possibility of using LM for a diversity of physiological measurements and healthcare, pioneering new avenues in subsequent circuit manufacturing technologies and the field of biomedical engineering. Being a natural conductor, liquid metal ink possesses distinctive characteristics like conductivity, wettability, printability, making it suitable for a multitude of emerging biomedical practices. Rebecca K. Kramer's team prepared EGaIn-thiol composite nanomaterials as small as 180 nm [44], demonstrating that they could be inkjet-printed onto nitrile gloves, which holds significant value for wearable devices and strain sensing monitoring. Yun et al. [45] utilized liquid metal EGaIn-based conductive materials as mechanical sensors, and their research showed that the degree of finger bending was reflected by the resistance changes in the LM-based composite materials, thereby monitoring motion changes. Commonly, through layer-by-layer assembly method, liquid metal could be formed in encapsulation layer to be used as sensors to detect the joint or plantar movement [29]. Furthermore, considering the power supply issue for electronic devices, Yang et al. prepared a stretchable

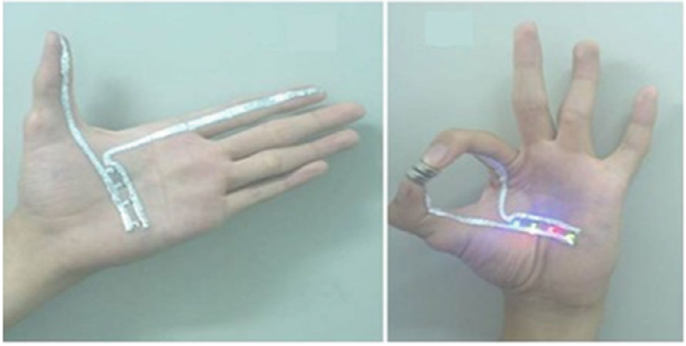

Fig. 5.4 Liquid metal as a display of skin electrons [43]. Reprinted under Creative Commons Attribution License

piezoelectric-enhanced device based on liquid metal electrodes [46], for mechanical energy harvesting and motion signal recognition; this self-powered approach aligns with the future direction of wireless, green, and sustainable development. Even under a 200% strain rate, the electrical resistance of electrodes fabricated with liquid metal is below 2.0 Ω. In addition, the output power density of the piezoelectric-augmented triboelectric nanogenerator can attain 1.1 mW/cm^2. Results of previous studies show that the elongation at break of the piezo—triboelectric nanogenerator can attain 645%. Both triboelectric and piezoelectric nanogenerators exhibit excellent performance in harvesting multivariable mechanical energy.

The development of liquid metal-based wearable systems is a key event in the integration of high-performance electronic skins. Guo et al. [47] utilized Cu-EGaIn to fabricate a stretchable electronic skin [47], combining water transfer and laser printing technologies. The resulting Cu-EGaIn electronic skin can be manufactured in seconds, significantly reducing production costs. In addition, the electronic skin maintains electrical stability on human skin. Its excellent electromechanical performance and radiographic imaging capabilities make it suitable for stretchable electronic devices, like interactive devices, flexible displays, for applications in temperature monitoring, interactive electronics, and CT-guided tissue biopsy. However, the limited printing resolution of laser printing and the insufficient breathability of the materials mean that forming higher precision patterns and improving the comfort of electronic skin materials are issues that need to be addressed. Despite revolutionary progress among the many materials used for electronic skins, liquid metal-based flexible sensors still exhibit lower sensitivity for the limited resistance change of liquid metal. Feng et al. [48] controlled crack formation by adjusting the spatial layout of liquid metal, using a Cr/Cu bi-phase pattern to fabricate liquid metal-based flexible sensor devices for ultra-sensitive electronic skins. This enhancement in the sensitivity of flexible electronics is a great boost for subsequent applications of liquid metal substrates. However, the addition of traditional rigid metals still limits its stretchability. Therefore, developing composite structures and systems with high sensitivity, a wide stress–strain range, and high conductivity remains a challenge.

Additionally, there has been extensive research on the formation methods for liquid metal-based flexible electronics, including photolithography, injection molding, roll coating, inkjet printing, extrusion printing, and direct writing. These techniques impose corresponding requirements on gallium-based liquid metal composites. In summary, the application and research of those metals in the area of flexible electronics are burgeoning rapidly. However, it is still necessary to select the most suitable, convenient, and cost-effective materials and methods, and to standardize them for practical applications.

Secondly, unlike the liquid metal mercury, gallium-based liquid metal possesses not only excellent fluidity and metallic properties but also superior resistance to radiation. Moreover, it has low volatility, good biocompatibility, and degradability, making it suitable for applications in biomedical engineering, including contrast agents [38], drug delivery, embolic agents, wound healing, electronic blood vessels, and antimicrobial applications [3]. When used as a high-density fluid material, it was reported that such kind of liquid metal has injectable properties and the capability to perform vascular angiography within vascular tissue. This offers a novel medical imaging technique beyond the traditional use of barium meals. Professor Liu Jing's team was the first to demonstrate its feasibility in imaging in 2014 [49, 50], and subsequently confirmed the biosafety of Ga as a contrast agent [38], among other contributions.

In 2015, Lu et al. [51] leveraged the deformability and size effects of liquid metal to employ it in a drug delivery system. By using simple ultrasonication, they obtained a core–shell nanostructure of GaIn and thiol-poly(ethylene glycol)-amine. Subsequently, they loaded doxorubicin (DOX) to achieve nanoparticles with mean diameter of 107 nm (Fig. 5.5). The study demonstrated that these gallium-based liquid metal nanoparticles, after being internalized by cells, facilitated the release of DOX in an acidic matrix and subsequently degraded on their own. This provides an excellent platform for nanoscale drug delivery, and further research is warranted, including the assessment of tissue/organ toxicity of the composite formulation, and other promising drug delivery systems made from various liquid metals and their impact on the elements in vivo (such as Fe or other metals). Of course, the conductivity of liquid metal (LM) can also be harnessed to explore multifunctional applications that combine drug release and sensing monitoring.

To combine the liquid metal with hydrogels can enhance its biocompatibility, thereby increasing the potential for biomedical applications. Fan et al. developed an injectable liquid metal-sodium alginate hydrogel as an embolic agent for the treatment of endovascular embolization and tumor embolization [18]. Moreover, it can be imaged using X-ray and CT scans to confirm the location of the material. This hydrogel can occlude arteries until they significantly caused ischemic necrosis of the tumor and some healthy tissue, achieving the purpose of treatment. This study shows that it is a convenient and fast method for therapeutic embolization, but more research is needed in terms of flexibility and controllability to meet clinical demands. In addition to in vivo composite gel applications, inspired by the talons of an eagle, Professor Zhao Yuanjin's team prepared a claw-like microneedle patch encapsulated with liquid metal [52] for accelerating wound healing. The microneedle patch

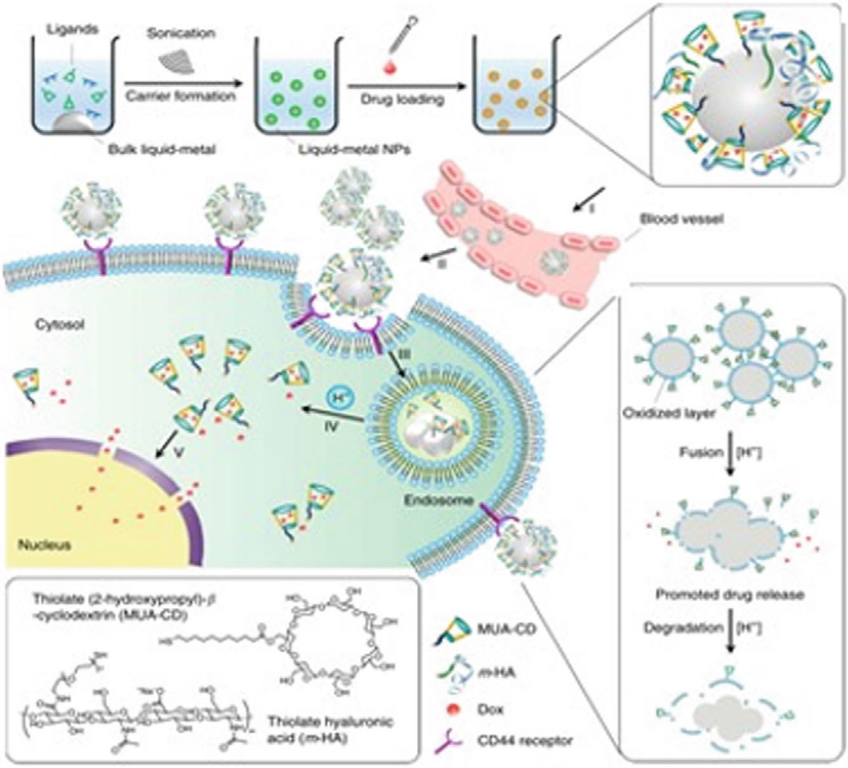

Fig. 5.5 Schematic design of the transformable liquid–metal delivery system [51]. Reprinted under Creative Commons Attribution License

contains two inclined hydrogel components and ventilated gauze. This microneedle tip forms a claw-like clamping structure, allowing the patch to adhere and fix the injured area, and prevent the wound from reopening. Studies have shown that due to the embedded W-shaped liquid metal (LM) connecting the tip of each microneedle part to an external power source, the microneedle patch can guide cell migration, promoting cell proliferation, and accelerating wound healing. This research demonstrates the higher performance of the electric patch, which can potentially be used in wearable home electrical stimulation devices and meet clinical demands. However, further in-depth study is necessary on the mechanical properties and repeatability of such electrode patches to better understand their performance.

Xingyu Jiang's team has utilized the high conductivity and biocompatibility of liquid metal to fabricate flexible electronic devices, creating electronic blood vessels. They have integrated conductive liquid metal-polymer circuits with a trilayer of vascular cells to surpass natural blood vessels [53] The study has demonstrated its feasibility, with superior biocompatibility, enabling electrical stimulation, and maintaining good patency in a rabbit model. This provides an excellent platform for personalized therapies in the future. Additionally, leveraging these advantages, the team has also developed flexible, degradable, and conductive vascular stents based on gallium-based liquid metal to prevent post-implantation tissue expansion [54]. This research can inspire the subsequent development of other implantable bioelectrical devices in area of gene therapy. Recently, Wang et al. [37] studied the blood biocompatibility of liquid metal including Ga/GaIn/GaInSn, it showed that these three liquid metals did not cause hemolysis and had a negligible effect on the components in the blood and serum. And Rao et al. researched the antimicrobial mechanism of liquid metal [55], indicating that liquid metal releases Ga3+ in solution, which generate free radicals that help kill bacteria, while Ga3+ themselves do not have this bactericidal effect. Undoubtedly, good biocompatibility coupled with strong antimicrobial properties will accelerate the application of gallium-based liquid metal in biomedical engineering.

The application of it in biomedical engineering showcases their unique properties and advantages, and ongoing exploration continues to broaden their potential uses in the field of biomedicine. Nevertheless, there is still a relative lack of understanding regarding the underlying mechanisms, and the translation of research into practical applications has a long way to go. This necessitates timely communication and collaboration between the academic and medical communities to facilitate progress.

Once again, the excellent flexibility, fluidity, thermal conductivity, electrical conductivity, and biocompatibility of it make the controllable actuation of liquid metals and their application in bionic robotics possible. In 2018, Wang et al. reviewed the applications of gallium-based liquid metals in flexible robotics [21], ranging from pneumatic actuators, soft robotic fish, electroactive polymer-based soft robots, to shape memory alloy materials, and biomimetic propulsive tissue-engineered jellyfish. It can be observed that the applications of it in this area are becoming increasingly diversified and functionalized.

Subsequently, Jing Liu's team incorporated ethanol into a mixture of GaIn and silicone rubber [56], creating a highly deformable liquid metal composite material. When heated, some ethanol droplets embedded in the composite can actuate by changing phases. This method, which does not require a complex operating system, enables remote wireless heating for 2D/3D shape transformation. Comparative tests have proven that free deformation behavior cannot be achieved without the addition of liquid metal. Based on the distributed decision-making present in octopus arms, Michael D. Dickey's research group first doped thermochromic materials into elastomeric silicone materials and then integrated liquid metal as a sensing composite into the material, resulting in a fully soft, stretchable, sensory, and color-changing silicone composite [57] (Fig. 5.6). This material can respond to temperature with visual display (from purple below 28 °C to blue between 28 and 37 °C to white above 37 °C) and deformation. It can also achieve specific responses under multiple sensing conditions, thus enabling remote control. It has potential applications in flexible camouflage, thermal imaging color strain sensing, and flexible tactile response devices. However, the sensor devices fabricated in the study are relatively thick, which is not conducive to comfort and flexibility when used on the skin. Further

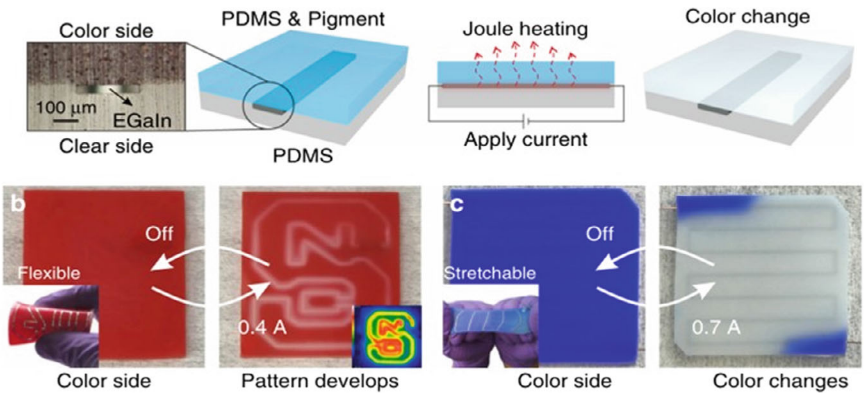

Fig. 5.6 Flexible tactile response device based on siloxane-LM composite [57]. Reprinted under Creative Commons Attribution License

investigation is needed into their practical applications in electronic skin and similar areas.

Due to the skin-friendly nature of hydrogels, recently, Chen et al. [58] prepared a PDA-GaIn-PNIPAM thermos-responsive hydrogel. Research indicates that this hydrogel can achieve rapid, tunable thermal response and directed motion. Under 45 °C stimulus, the hydrogel with a low content of PDA undergoes rapid unidirectional bending, while the hydrogel with high ratio of PDA exhibits sequential bidirectional actuation. Therefore, the motion is associated with the content of PDA, which has good repeatability and is suitable for manufacturing temperature-controlled multifunctional mechanical hands, soft robots, multifunctional sensors, etc. Recently, Wang et al. [59] reported a composite material of liquid metal and Fe. Utilizing its phase change characteristics, it can grasp both magnetic and non-magnetic materials, earning the nickname "Master Magnet." This is an interesting phenomenon and application, adding promise to the controllable regulation of soft robots and holding potential for translation into practical product applications.

It is well known that liquid metals are limited to a high-reflectivity, shiny silver-white color, which is singular and disadvantageous for camouflage in soft-bodied animals found in nature. Hou et al. [60] reported on bionic colored liquid metal soft robots with tunable structural colors. When liquid metal is mixed with Al foil in electrolyte solution, the surface color of liquid metal can transition from white to gold and black. Under the modulation of an electric field, a stable liquid metal functional material was achieved. Characterization revealed that its surface nanoscale Ga2O3 film gives it the ability to display multiple colors. When liquid metal is put on graphite surface, the surface oxide layer Ga_2O_3 scatters light, and when the liquid metal undergoes electrolysis, thin-film interference triggers rainbow colors. This study provides a concept for preparing colorful liquid metals and diversifies their applications, especially in enhancing the design of soft robots using smart camouflage functions. Currently, research in bionic robots is at a stage where they can grasp, change color, and move. Studies on the bionic preparation of large-scale organ tissues and multifunctional sensing are still being continuously explored and innovated.

5.4 Conclusion

The unique physicochemical properties of liquid metals provide great potentials for next-generation wearable sensing technologies. The gallium-based liquid metals largely improve the flexibility of circuits. In addition, they herald new applications in nanogenerators, ultra-sensitive electronic skins, and electronic blood vessels. Despite the advancements, there are many unknown functional forming methods and properties that deserve further investigation. The liquid metals will continue reshaping the landscape of wearable sensing technologies, by improving the performance and user experience.

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Chapter 6
Accelerometry in Monitoring Physical Activities of Young Children: Technical Advancements and Concerns in Real-World Applications

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Abstract This chapter provides an overview of the use of accelerometery to assess physical activity with a specific focus on working with children and young people. The chapter introduces how accelerometery has been used with pediatric populations alongside an overview of the technical decisions that researchers need to consider when wanting to capture physical activity and movement data with children and young people. Case study information is provided showcasing how accelerometer calibration and validation might be best performed when working with children, followed by guidance and strategies to maximise the data collection process when using accelerometery with children.

6.1 Introduction

The use of accelerometers within research examining movement behaviours, movement quality and physical activity assessment has become commonplace over the last two decades. In the context of physical activity assessment, accelerometers provide objective data related to the range of movement variables, including time

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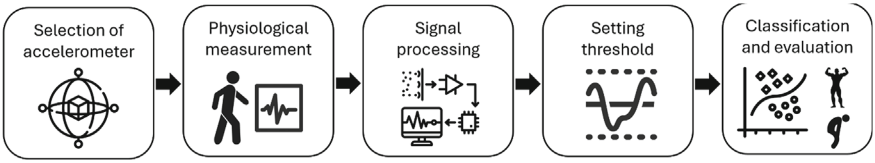

Fig. 6.1 Workflow of accelerometer-based analysis of physical activities, icons from Microsoft Powerpoint, icons8.com, freepik.com, and flaticon.com under free license

spent in sedentary behaviours, time in moderate and vigorous intensity physical activity (MVPA), physical activity energy expenditure and sleep related behaviours [1]. An accelerometer is a wearable sensor that measures the accelerations of the body, or body segment to which it is attached. Three-dimensional accelerations can be used in the detection of multiple physiological parameters including gait, heart rate, and respiratory rate [2]. Accelerometers are sensitive to minor movement, therefore can be used as reference sensors in the removal of motion artifact [3]. There are a number of commercial accelerometers available, such as Actigraph, Axivity and GeneActiv, which are well validated in terms of physical activity assessment. Whichever brand of accelerometer is utilised, the signals undergo filtering and preprocessing by the device, from which different metrics relating to physical activity and movement behaviour can be obtained. Typically, cut-points or thresholds are employed to distinguish different intensities of physical activity, or different types of movement behaviours. Such cut-points are specific a number of other aspects related to accelerometer use for capture of physical activity data, such as sampling frequency and epoch length amongst other considerations. The cut-points in parallel with artificial intelligence based classification results can be used for the evaluation of physical activities and health status (Fig. 6.1). A comprehensive overview of these decisions can be found in the review by Migueles et al. [1], so will not be discussed in depth in this chapter.

The field of accelerometery for physical activity assessment has evolved rapidly resulting in an abundance of information on the topic, but little consensus has been achieved on best practice, which differs depending on the target population of interest. This chapter specifically focuses on the application of accelerometery with children, and while accelerometers overcome known barriers to gathering physical activity data in children by other methods, such as self report [4], the use of accelerometers in pediatric population requires particular thought as children are not simply adults in smaller bodies, their physical activity habits and patterns of movement differ. As such there are different considerations needed when using accelerometers in this population compared to adults.

6.2 Technical Decisions

There are a number of technical decisions that need to be taken when utilising accelerometers with children. These related to device placement, sampling frequency, filtering, epoch length, and non wear time definitions and wear time protocols. All can impact the output derived from an accelerometer.

Typically, these devices have been worn on the hip or wrist when quantifying children's movement behaviours [1], while the early stages of accelerometer based physical activity research tended to use hip worn devices in the majority [5], although there are some studies that demonstrate efficacy when the device is worn on the ankle [6]. There is good evidence that both hip and wrist worn accelerometers produce valid data in children [7], and choice of cut-point in subsequent analysis should reflect the wear location. However, there is some data suggesting that compliance to wear time protocols is higher for wrist worn compared to hip worn accelerometers in this population. Lack of compliance for hip-worn studies was typically found in studies where participants are asked to take the accelerometer off when going to bed [7] and hip-worn accelerometers are also limited when trying to capture upper body movements [8]. This latter point is particularly pertinent in children, where object control skills, such as throwing and catching are prevalent and account for a high proportion of energy expenditure [8]. Despite this, there remains no consensus regarding whether hip or wrist placement provides the more accurate assessment of children's physical activity.

There are not a substantial number of studies which have examined effects of sampling frequency on physical activity metrics in children. However, as the nature of children's physical activity is more sporadic and intermittent than that of adults [9, 10], sampling frequency will likely impact any estimates derived from accelerometery. Typically, sampling frequency for commercially available accelerometery sits between 30 and 100 Hz and Brønd and Arvidsson [11] have demonstrated that activity counts from the same accelerometer differ depending on sampling frequency, with activity counts being higher with high sampling frequency. Likewise, Migueles et al. [1] highlight that the original filtering processes for physical activity assessment using accelerometery was based on 30 Hz, so while a higher sampling frequency may better capture the nature of children's physical activity more effectively, using frequencies sin multiples of 30 may provide a better metric [11]. The key message for researchers when considering sampling frequency should be: use the frequency suggested by the selected validated method or results from accelerometer derived assessment will be biased.

As with sampling frequency, there is little data pertaining to how filtering impacts assessments of physical activity using accelerometers in children. Given such filters are in built into the software provided by commercially available accelerometers (e.g., Actigraph) and are proprietary in nature, researchers should be aware when such filtering takes place, as there are differences in output when different filters are applied to children's PA data. It is also known that for Actigraph accelerometers, the filter is set at 2.5 Hz, yet human movement can occur at up to 3.4 Hz, so in certain circumstances, there is potential that some vigorous activity may be underestimated when using this model of accelerometer [12]. Epoch length, likewise can impact the outputs derived from accelerometery and typically smaller epoch lengths have been employed in pediatric studies on the basis that a smaller epoch length is likely to better capture the intermittent nature of children's physical activity more effectively [9, 10]. Typically, epoch lengths of 5 s have been employed in younger children (up to 8/9 years of age) and slightly longer epochs of 15 s have been employed with adolescents [13]. This is in comparison to adult based studies where epoch length are rarely considered [1]. The most recently developed cut-points to assess children generally involve 1 s epochs to account for the sporadic and intermittent changes in PA intensity typically observed in children [9, 10]. Non wear time is also a consideration that needs to be made when using accelerometers. Non wear time refers to the amount of time where the accelerometers is not worn during an assessment period and which is subsequently excluded from analysis. This could be for activities such as swimming, or when the participant is showering/bathing as examples. There is no consensus on what amount of time of consecutive zeros constitutes appropriate wear time for children specifically. In adults 90 min has tended to be recommended, but there is no such recommendations for pediatric studies. Often researchers employ the non wear time duration for adult studies to their data. This can however be problematic as research demonstrates that, in children, as non wear time increases, the number of activity counts derived from the accelerometer decreases [14].

Other aspects should be considered when using accelerometers to obtain an estimate of the true physical activity undertaken in children such as the wear time protocol. Wear time protocols consider valid wear time criteria, valid day criteria and valid week criteria. Wear time criteria have been created to distinguish between periods where an individual is not moving (e.g. sleeping, watching TV) from periods when an individual is not wearing the accelerometer [1, 15]. The criteria for what constitutes a valid day are also important, and typically, at least 10 h of valid wear time are recommended when assessing children during their wake time [1, 15]. Alongside valid day criteria, the number of days of monitoring which constitutes a valid week also need to be considered. It has been suggested at least four valid days of accelerometer data are needed to constitute a valid week [1, 15]. To obtain a robust assessment of physical activity in children, researchers need to understand and be clear regarding their decisions on such wear time as collecting data on a shorter day, or a smaller number of days in any given week may not provide a representative assessment of a child's physical activity behaviour.

6.3 Issues with Classifying Accelerometer Derived Physical Activity Using Cut-Points

One of the ongoing debates when using accelerometers to assess physical activity in children relates to the use of cut-points to determine intensities of physical activity. It is well known that use of inappropriate cut-points can lead to bias and misclassification of data derived from accelerometers [16]. In this context, the term ‘inappropriate’ may refer to cut points developed on adults and applied to children, of use of cut points validated for us eon the hip but applied to wrist worn data. Data also demonstrate that physical activity can be drastically misclassified from use of different cut-point sin children’s physical activity data. As an example, when trying to determine the prevalence of children achieving 60-min moderate to vigorous physical activity, Migueles et al. [17] found that, the same data resulted in between 8 and 96% of children achieving the 60 min threshold depending on which cut-point was employed. That is not to suggest cut-points are without value, it is more a case that researchers need to be clear on which decisions they make regarding cut-point choice and use. Researchers need to be cognisant that calibration of accelerometer cut-points and subsequent validation is specific to the population initially employed for calibration and the protocol used for calibration. We highlight some of these issues in the case study below.

6.4 Case Study: The Importance of Protocol in Accelerometer Calibration [6]

Accelerometer cut-points used to classify physical activity in children have generally followed a standard process involving children performing an activity bout of a set duration in a set order, usually beginning with a sedentary activity (seated rest) and progressing into different intensities of locomotor activity, usually walking, jogging and running. While this may be logical for adult based calibration, as locomotor activity is the predominant form of activity for adults, this is not the case for children. Children typically engage in a wider range of activity behaviours than adults, for example in playground activities that are highly intermittent and stop-start in nature, and accelerometer calibration has been criticised for not including tasks such as cycling and those involving the upper body [18]. Fundamental movement skills, such as throwing, kicking, catching are especially important here as, they are a key feature of children’s movement activity [19]. Data also suggest that existing cut-points underestimate physical activity in children where throwing/catching is involved [20].

As a result Duncan et al. [6] undertook a calibration and cross validation of accelerometer cut-points using the GeneActiv accelerometer. In their study, they asked 20, 8–12 year old children to wear accelerometers on both wrists, waist and both ankles, whilst performing five minute bouts of the following: lying supine, standing, a medium paced run (4.5 kmph^{-1}), instep passing a football (at slow and fast cadences) and dribbling a football (at slow and fast cadences). Children's actual level of physical activity (via metabolic equivalents) was also assessed using indirect calorimetry during these activities.

Following the activities, receiver operating curve analysis was performed with this data set to establish accelerometer cut points reflecting sedentary behaviour, light, moderate and vigorous physical activity, with the standard process used for accelerometer cut-point calibration.

However, following this process, Duncan et al. [6] used a secondary data set comprising data from 30, 8–11 year old children and comprising accelerometer and indirect calorimetry data from the following: Lying seated, playing with Lego, slow walking (3 kph^{-1}), medium paced run (4.5 kph^{-1}), fast paced run (6 kph^{-1}), overarm throwing and catching a standard size tennis ball (20 passes per minute) and instep passing a football (size 3, 20 passes per minute). When applying their cut points to this data set ROC curve analysis indicated that the cut-points derived in the Duncan et al. [6] study were able to successfully discriminate sedentary behaviour, light physical activity and moderate physical activity in this independent data set.

The two step process employed in the Duncan et al. [6] study is important because, the protocols employed, non-traditional movements which children typically engage in. The calibration and cross validation samples incorporated different movements from each other, but both incorporated movements that were not solely locomotor in nature. Moreover, the focus of calibration and then cross validation of cut-points using an independent sample, in the same study should be considered good practice as it provides calibration and independent cross validation together, reflecting the specific of the population of interest.

6.5 Moving Away from Cut-Points?

While accelerometer cut-points are widely used and important in establishing prevalence of children meeting or not meeting physical activity guidelines for health, there is a recognition that accelerometer metrics can move beyond cut-points. Traditionally, accelerometer output has been transformed into proprietary counts [5]. However, the algorithms used to create physical activity count data within different brands of accelerometer made it difficult, if not impossible, to compare results collected from different devices. As a result, the use of raw acceleration output has subsequently been advocated [21]. Within the last decade open science processes have enabled researchers to move beyond proprietary algorithms for accelerometer data and can generate a range of different metrics based on raw acceleration data. The most popular of these, GGIR *(*https://cran.r-project.org/web/packages/GGIR/index.html) using the package R has enabled production of variables such as: Euclidean Norm Minus one (ENMO) and mean amplitude deviation (MAD) [17, 22]. Using ENMO or MAD metrics can facilitate the comparison between accelerometer outputs derived from different accelerometers brands and consequently it could help comparing physical activity measurements reported in different studies.

There have been other, cut-point free, raw acceleration derived metrics that provide alternatives compared to cut-point based assessment of physical activity [23]. Examples of these metrics are: the average acceleration over 24 h, intensity gradient, the lowest acceleration over the most active hour, and the lowest acceleration over the most active half hour in a day [23, 24]. The average acceleration over 24 h as well as intensity gradient differ from PA intensity assessment as they represent the magnitude of total PA accumulated during the recording time [24]. Of particular relevance to this chapter the average acceleration over 24 h as well as intensity gradient have been found to be positively associated with health-related outcomes in children [24]. Such open source methods allow for harmonisation of accelerometer data collected using different accelerometers with subsequent reference values [25] and visualisation tools have also been developed which aid interpretation of raw accelerometer data in the context of physical activity.

When communicating the results of accelerometer data to children (and parents, such outcome data may be more useful that cut-point based data alone. Single value summary outcomes provide a top level overview of physical activity over a set period (eg a day, a week) and can be useful for tracking physical activity changes over time. Patterning outcomes are slightly different and provide information on whether the physical activity was undertaken in one bout, or accumulate din smaller bouts throughout a day, or week. In the case of children's physical activity data, where children are more sporadic and intermittent in terms of the physical activity they undertake, patterning outcome data may be particularly useful as a way to use accelerometers to understand children's physical activity.

While open source and cut-point free accelerometer metrics are attractive and the use of GGIR and other related programmes in R theoretically makes such metrics available for all there remain barriers to accessibility and the technical skill to use some of the programmes needed to produce such metrics [26]. In addition, recently development of artificial intelligence (AI) enables the automatic accelerometer-based classification of physical activities using machine learning [27] and deep learning [28]. However, many AI models are less transparent and explainable compared with traditional cut-point methods. In addition, they require high computational resources. Another promising approach is AI-assisted data fusion which combines the data derived from accelerometer and other sensors into a feature metrics to achieve reliable classification of physical activities [29]. Further investigation is warranted towards automatic, reliable, and explainable classification of physical activities.

6.6 Practical Considerations When Using Accelerometery with Children

While there are a number of technical decisions that researchers need to make when using accelerometers with children and young people in order to obtain robust data, such as those explored above, there are also key practical considerations which researchers also need to take account of to ensure robust data collection. These practical considerations are often overlooked, especially when the researchers involved have not worked with children previously. Such practical considerations relate to: participant driven compliance strategies; reasons for non compliance; strategies for accelerometer care and; reasons for non compliance to specific study conditions. Duncan et al. [30] and McCann et al. [31] have provided some practical strategies to help ensure compliance to accelerometer wear time and data collection when undertaking research in children. These considerations are summarised in Table 6.1.

Table 6.1 Strategies to ensure compliance to accelerometer wear protocols in children and young people (adapted from Duncan et al. [30], and McCann et al. [31])

Compliance	
Forc children	• Sticky note reminders (attached to a prominent place in the home) • Mobile phone reminders • Social conformity (adherence was more likely if peer groups engaged in the study together)
For adolescents	• Social conformity • Mobile phone reminders • Monetary compensation (for achieving wear time thresholds)
Recruitment	
For children and adolescents	• Social conformity: Where possible target friendship groups (e.g., recruit from the same school class/sets) to ensure shared norms and behavioural reinforcement
Parents and gatekeepers	• Invite parents/guardians to a social discussion about the research, including showing them, letting them handle the accelerometers. Remind them of the positive aspects of the study and why adhering to study protocol is important
Accelerometer care	
For children and adolescents	• When introducing the accelerometers, to instil a sense of trust, inform children that the accelerometers belong to the researchers/institution and they are being asked to take care of them. Make sure the children understand the value of each accelerometery by using references they relate to, e.g., that each accelerometer costs the equivalent of a playstation or xbox, so they should take good care of it

6.7 Conclusions

Accelerometers provide excellent opportunity to quantify movement behaviour in children and young people. However, researchers wishing to use accelerometery to assess physical activity, or other movement behaviours in children or young people need to understand the key technical decisions that are needed to use accelerometers to gather valid and reliable physical activity information. Children and young people's physical activity is qualitatively different to that of adults, tending to be more intermittent and sporadic in nature. Technical decisions around accelerometer operationalisation and subsequent post data collection analysis should reflect these differences and process undertaken for accelerometer assessment should be specific to the population being studied.

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Chapter 7
Automated Detection of Shockable Ventricular Arrhythmias Using ECG Signals

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Abstract Shockable ventricular arrhythmias are life-threatening conditions that can arise from congenital or acquired causes. Healthcare providers rely predominately on electrographic criteria and disease-specific scoring systems. However, these methods are susceptible to reduced accuracy due to discrepancies in electrocardiogram (ECG) interpretation, systemic bias and observation of a limited number of predictors. The recent development of automated detection of shockable ventricular arrhythmias through machine and deep learning approaches demonstrates a promising solution to previous limitations. Current research has investigated artificial intelligence (AI)-based models for the classification and prediction of shockable ventricular arrhythmias using ECG signals. The clinical implications of AI techniques allow patients to receive timely medical interventions including defibrillation therapy and anti-arrhythmic drug prescriptions, ultimately improving patient mortality. However, the

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conventional use of automated approaches is restricted due to the absence of a standardized regulatory framework and the general obscurity of the technology. Thus, this chapter aims to review the existing evidence of AI-based approaches to the detection of shockable ventricular arrhythmias using ECG signals. Current literature suggests that a diverse range of AI models show improvement in the accuracy of disease detection and identification of significant predictors. However, further research comparing the performance of current detection methods versus AI approaches is required.

Keywords Shockable · Ventricular · Arrhythmias · Electrocardiography

7.1 Introduction

Sudden cardiac death (SCD) is characterized by an unexpected loss in heart function due to irregular electrical signaling activity. It can be due to coronary artery disease (CAD) and valvular heart diseases [1]. Moreover, risk factors such as hypertension, obesity and diabetes mellitus are strongly associated with increased propensity to SCD [2–4]. Rarely, SCD can be caused by congenital arrhythmic syndromes that include ion channelopathies [5–8] and cardiomyopathies [9–11]. It is estimated that 4–5 million deaths every year are a result of SCD [12]. In which, 80% of SCD patients have been identified with VT [13]. To determine whether the cardiac arrest is a result of a non-shockable or shockable arrhythmia, an electrocardiogram (ECG) is used. Shockable ventricular arrhythmias can be divided into two main types: ventricular fibrillation (VF), which is characterized by the presence of irregular or rapid QRS complexes and ventricular tachycardia (VT), which is characterized by rapid, regular and broad QRS complexes with a QRS duration longer than 120 ms [14]. Patients suffering from VT/VF require immediate defibrillation or electric shock therapy. For every minute delay in defibrillation, the treatment effectiveness is reduced by 10% [15].

As the majority of SCD cases occur outside of a hospital setting, healthcare providers must diagnose and deliver treatment within an extremely narrow time frame to avert any life-threatening complications and possibly death. In emergency settings, analysis of the electrical rhythm is performed either by the defibrillation algorithm of an automated external defibrillator (AED) or by a physician [16]. In some European hospitals, manual defibrillators are more commonly used than AEDs [17]. However, there is a paucity of literature exploring the performance of emergency physicians in differentiating shockable and non-shockable ventricular arrhythmias. An observational study by Derkenne et al. found that although the performance of physicians was faster and more sensitive for VT identification compared to an AED, their performance had reduced sensitivity and specificity to fine VF identification [16]. This is because it is difficult to manually identify VT/VF features when the ECG waveforms are irregular, fluctuating and corrupted by noise. In addition, the feasibility of shockable VA detection during cardiopulmonary resuscitations (CPR) remains challenging, as this compromises the patient's survival [18]. Thus, to optimize the discrimination between shockable and non-shockable ventricular arrhythmias, many researchers have begun to explore the use of automated algorithms as an alternative detection tool. Automated algorithms refer to a series of artificial intelligence (AI) based models designed to produce highly sophisticated and accurate functions with little human intervention. AI can be divided into two main approaches: machine learning (ML) and deep learning (DL). In the literature, studies have developed AI-based classification and detection algorithms for shockable ventricular arrhythmias using cardiac signals. With the continual improvement of AI-based differential diagnosis between shockable and non-shockable ventricular arrhythmias, the involvement of automated systems will enhance clinical decisions, allowing patients to receive appropriate care and ultimately reduce the mortality rate of SCD.

The recent development of AI has demonstrated potential in addressing global healthcare issues in various medical fields such as primary care [19, 20], paediatrics [21, 22] and medicinal chemistry [23, 24]. In cardiology, AI-assisted prediction of cardiac arrests, cardiovascular signal analysis and facilitation of precision cardiovascular medicine has been used in different patient settings [25–27]. For example, AI has been used for the purposes of diagnosis [28, 29], risk stratification and determining prognosis [30–32]. Hence, it has become increasingly pertinent to understand the vast clinical applications of AI technology. To corroborate, the general obscurity surrounding the AI algorithm usage due to a lack of a standardized framework may overshadow its clinical implication in the long term. Therefore, this chapter aims to discuss the contemporary literature regarding the use of different AI approaches in the detection of shockable ventricular arrhythmias using ECG signals (Fig. 7.1).

7.1.1 Machine Learning and Deep Learning

Both ML and DL algorithms may be deployed for discriminating shockable and non-shockable ventricular arrhythmia. Literature research has demonstrated that the majority of AI techniques in the detection of shockable and non-shockable ventricular arrhythmias are traditional ML approaches where ECG signals are processed with a standardized workflow [33]. To develop an algorithm, specific diagnostic features are extracted from pre-processed ECG signals and fed into the classifiers to learn how to classify diseases. Then, repeated exposure to large amounts of data will train the algorithm to become more accurate and refined.

ML models require sophisticated programming to perform classification and feature extraction tasks. The technology can expand beyond the functions of traditional statistical approaches as it can identify high-order interactions and nonlinear relationships between variables [34]. In contrast, these functions can be automatically performed using DL models, which mimic the learning capabilities of the human neural network [35]. A DL model is typically composed of a form of artificial neural network (ANN) coupled with hidden layers of increasingly complex and

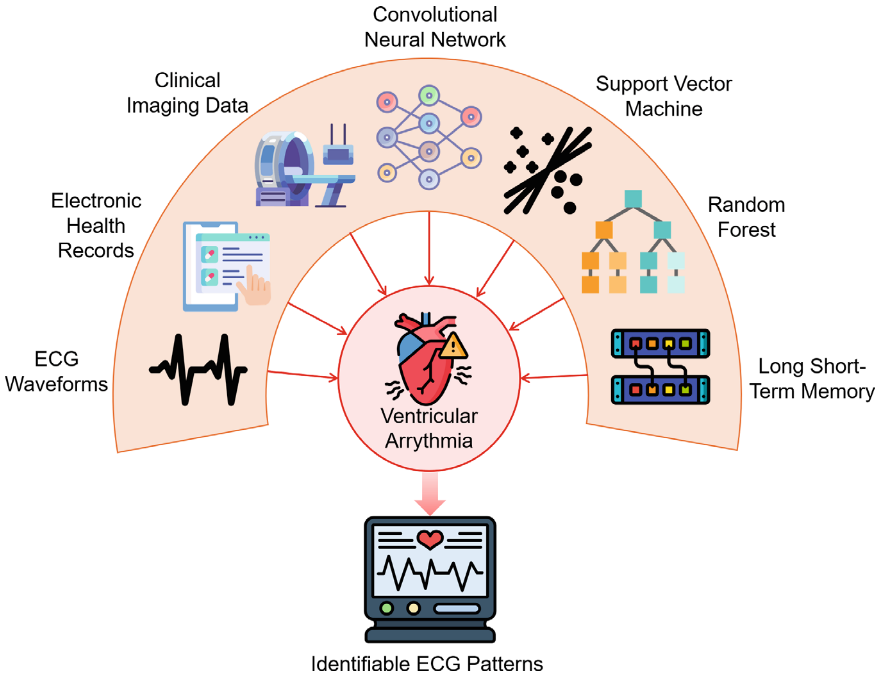

Fig. 7.1 Summary of different artificial intelligence approaches for the identification of shockable rhythms from electrocardiogram (ECG) recordings, icons from Microsoft PowerPoint and www.flaticon.com under Free License. CNN: convoluted neural network

abstract data representations. Its computational power far exceeds an ML algorithm and can leverage large, complex datasets to make effective decisions.

Although the idea of automated ECG interpretation has already existed for several decades [36], it was only through the relatively recent introduction of integrating large amounts of electronic health records into databases that revolutionized AI development in cardiac electrophysiology [37]. In addition to medical records, digital biomedical data of cardiac signals can be collected through wearable devices, mobile phone software and ECG monitors. A comprehensive analysis of all available data by a skilled expert is not feasible due to constraints in time and resource accessibility. Instead, these increasing quantities of datasets have propelled the training and refinement of AI algorithms, altering the landscape of disease detection in cardiac electrophysiology.

7.1.2 Convolutional Neural Network

The architecture of convolutional neural networks (CNNs) is inspired by the functions of the human visual cortex. The system is based on the fundamental idea of template matching, where objects of simpler nature are identified in the superficial layers and combine the analysis of more complex features in deep layers to generate a decision. In cardiology, this technique is commonly used in performing feature extraction and classification of visual data such as ECGs, X-ray records and echocardiography videos [38]. It is through training that allows CNNs to adaptively recognize the optimum significance of each respective layer, forming a concept of a spatial hierarchy of characteristics [39]. Recent CNN approaches offer a meaningful attempt at classifying shockable ventricular arrhythmias better than existing algorithms or cardiologists [40–42].

Nasimi et al. proposed a lightweight DL algorithm implementable on an automated external defibrillator (LDIAED) algorithm that can distinguish a 1.4-s segment of shockable signals from non-shockable signals with an accuracy of 99.1%. This system is based on a deep CNN model that does not require any preprocessing of raw ECG signals [43]. In another study, multiscale analysis of ECG signals was performed using the fixed frequency range empirical wavelet transform (FFREWT) filter bank [44]. The analyzed data is then inputted into a deep CNN for the detection of shockable ventricular arrhythmia. An accuracy of 99.0, 81.3 and 99.8% was achieved when comparing the detection of shockable versus non-shockable, VT versus VF and VF versus Non-VF, respectively. Some studies have designed 11 layered CNN algorithms that segment 2-s ECG segments to capture readings of shockable rhythm 2–4 times faster than traditional techniques [33].

7.1.3 Support Vector Machine

Support vector machine (SVM) learning is a type of ML approach that performs pattern recognition and categorization. It aims to separate data on an optimal hyperplane, where the distance between the closest data points of each class, known as support vectors, is maximized [45]. In cardiology, SVM classifiers have been used substantially for cardiac signal processing in the context of beat detection, wave delineation and general arrhythmia detection [46–48]. However, there is limited literature surrounding the use of SVM algorithms in the detection of shockable ventricular arrhythmias. Several studies have recently evaluated the integral role of SVM in the detection of VT/VF [49, 50]. Sharma et al. trained an SVM using ECG signals extracted from three-band wavelet decomposition filter banks to distinguish shockable and non-shockable arrhythmias [51]. The system achieved an accuracy and sensitivity of 98.9 and 99.1%, respectively. Researchers proposed to use this algorithm for the emergency revival of patients in cardiac arrest by employing the system in automated defibrillators. Alonso-Atienza et al. combined the use of an SVM algorithm and a novel feature selection methodology that can depict the relevance of 13 ECG parameters during the detection of shockable ventricular arrhythmias [52]. Within the 13 computed parameters, VF leakage (VFleak), spectral entropy (SpEn) and threshold crossing sample count (TCSC) demonstrated superior diagnostic properties, which align with the results of previous studies [53, 54].

Public or propriety databases host a large selection of long-term ECG recordings, allowing the identification of shockable events. Many AI models utilize these datasets for training [41, 55]. While records present VF with a coarse amplitude and high fibrillation frequency, ECGs recorded during out-of-hospital cardiac arrest (OHCA) present VF with smaller fibrillation frequencies and amplitude. This may be attributed to the fact that ECG signals are generally recorded 5–10 minutes later after the onset of the cardiac arrest, in which by then the ECG rhythm would have gradually deteriorated. Therefore, to optimize the generalizability and reproducibility of AI models for real-life AED use, one study utilized data from patients who OHCA. Interestingly, six ECG features namely $\times 1$, Hilbert transform (HILB), bandwidth-crossing percentage (bCP), sample (SamEn), phase space reconstruction (PSR) and bandwidth time feature (bWT) demonstrated a sensitivity of over 90%, while other features namely mean absolute value (MAV), VFleak and TCSC showed superior performance when trained with data from public databases [56]. In addition, amongst the five tested algorithms, the SVM displayed the lowest balanced error rate. Hence, the study highlights that incorporating other sources of ECG data can enhance the sensitivity and capabilities of AI systems for detecting shockable rhythms.

7.1.4 Random Forest

Random forest (RF) classifiers are composed of a collection of decision trees, as an input transverse through the tree network, the piece of information continues to get divided until it reaches the purest form of a subgroup. The current literature suggests that RF classifiers can effectively predict and offer novel characterizations of cardiovascular diseases [57–59]. However, the use of RF algorithms in the classification of shockable and non-shockable ventricular arrhythmias remains relatively unexplored [60]. Tripathy et al. demonstrated the use of an RF classifier to detect shockable ventricular arrhythmia with an accuracy of 94.4% using 8-s ECG data segments. The diagnostic features were extracted using the variational mode decomposition (VMD) technique which evaluates three modes of the ECG signal (Fig. 7.2) [61]. To corroborate, Verma et al. used an RF classifier to extract 17 ECG features and obtained an accuracy of 97.2% in the detection of VF. This study further supports that using an 8-s window length segment provided optimal results [62]. Moreover, some researchers have also applied RF models to identify the relative importance of various predictors regarding the survival of OHCA patients with shockable rhythm [63]. This includes age, presence of defibrillation, time to defibrillation, time from cardiac arrest to CPR and location of cardiac arrest, which reaffirms the results of previous studies [64–66]. A separate study combined the use of decision trees and an SVM classifier, which yielded a greater accuracy in detecting VT/VF compared to using an SVM classifier alone [67]. The method utilized only 5 s of ECG data and a total of 24 temporal and spectral features to discriminate VT and VF conditions.

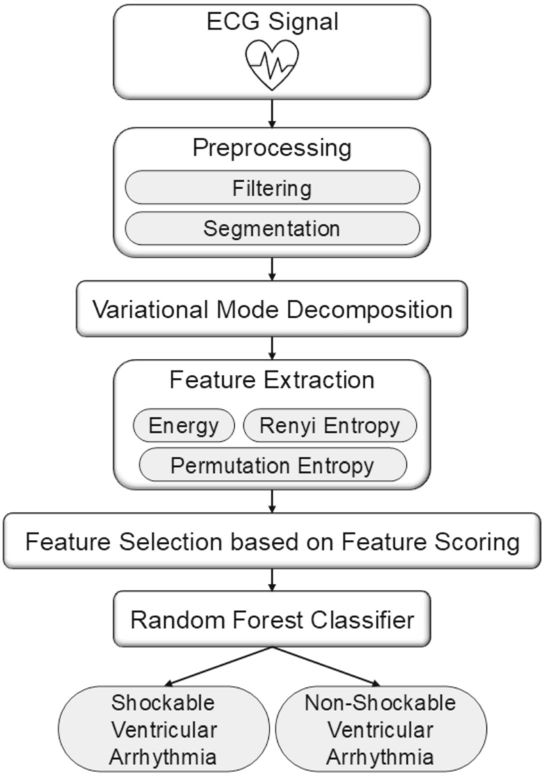

Fig. 7.2 Application of random forest machine learning model in the classification of shockable and non-shockable ventricular arrythmias based on ECG data. Redrawn from the workflow of [61] with Microsoft PowerPoint

7.1.5 Long Short-Term Memory

Long short-term memory (LSTM) models are designed for recognizing long-range dependencies and temporal sequences. The algorithm consists of memory blocks and a gating mechanism that regulates the flow and storage of information [68]. In recent years, LSTM has been increasingly applied for myocardial infarction (MI) classification, heart rate variability-based sleep stage classification and atrial fibrillation (AF) detection [69–71]. For ECG signal processing, many existing LSTM models are applied in conjunction with other AI models [72].

One key problem that arises using AEDs to classify shockable rhythms is the presence of CPR artefacts during chest compressions, which overrides the ECG morphological features. To mitigate the issue of ECG artefacts, one study developed an AI algorithm that could classify shockable and non-shockable rhythms in the presence of CPR without using a reference signal [73]. This algorithm is composed of the bidirectional long-short-term memory (BiLSTM) architecture, CNN and the residual connection layer. Subsequently, there is no need to interrupt CPR whilst effectively analyzing for shockable rhythms, thereby minimizing potential end-organ damage

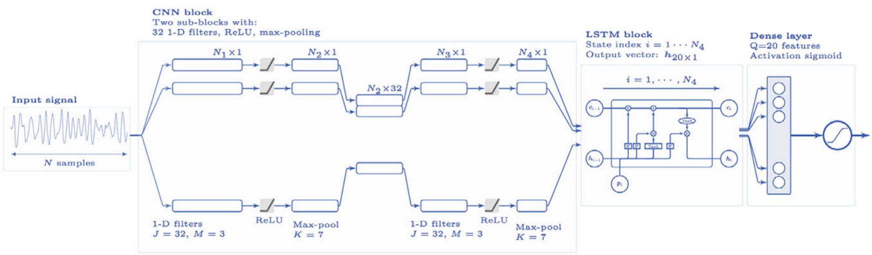

Fig. 7.3 Visual representation of a deep learning network for diagnosing lethal ventricular arrhythmia based on ECG signals. The architecture has three blocks: a convolutional block (CNN), a recursive block (LSTM), and a final decision stage based on a neural network. Reproduced from [76] with permission under CC BY 4.0 Copyright License

and permanent complications [74]. Alternatively, some studies use adaptive filters to model and remove CPR artefacts prior to performing the rhythm classification, but still achieve a high degree of detection accuracy [75]. Picon et al. implemented an algorithm combining LSTM and CNN to detect lethal ventricular arrhythmias using OHCA data. The model can effectively distinguish shockable and non-shockable rhythms using 3-s ECG segments (Fig. 7.3) [76]. On the contrary, some studies showed poor performance in VT classification in all six models including LSTM, residual networks and hybrid LSTM-CNN models. The researchers noted that this could be attributed to the low support in the dataset and using only short ECG data samples to train the algorithm [77].

7.1.6 Discussion

Several ML and DL approaches have been proposed in the current literature to overcome the constraints of traditional ECG signal processing methodologies such as manual reading. In an acute setting, ML and DL algorithms can facilitate the rapid identification of patients with fatal VT/VF who are at imminent risk of SCD. Automation development has prompted the contemplation of advanced therapeutic approaches and classification strategies of cardiac diseases. Personalized clinical support and predictive analytics for medical risk identification using AI are believed to be superior to human capabilities [78]. One study compared the performance of seven ML algorithms in detecting VF based on a single feature or a combination of VF features. The results highlighted that NN, RF and SVM classifiers exhibited improvement greater than 5% in predicting defibrillation success using feature combination compared to using a single VF feature (Fig. 7.4) [79]. Similarly, a method deploying a deep neural network architecture examined various hybrid time–frequency-based features in ECG signal analysis. The method achieved an accuracy of 99.2% when characterizing between VT and VF [55]. Resultantly, AI can help to further personalize patient care and identify needs for electric shock therapy or other treatment

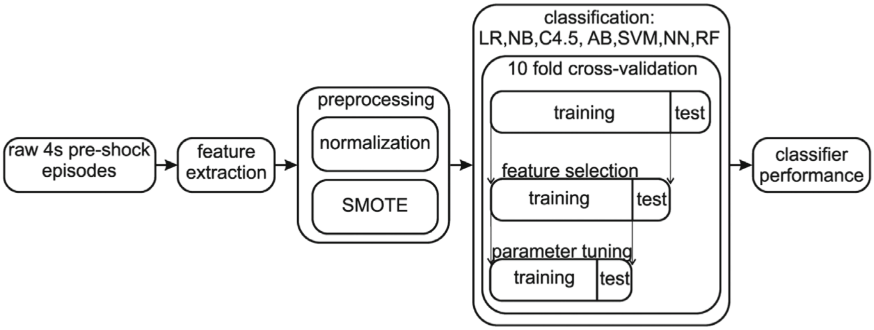

Fig. 7.4 The ECG features extracted pre-shock episodes were utilized for predicting defibrillation success in out-of-hospital cardiac arrested patients. Synthetic Minority Oversampling Technique (SMOTE) was performed for balancing the successful and unsuccessful defibrillation class distributions. Different ML algorithms were utilized for feature selection and classification. Reproduced from [79] with permission under CC BY 3.0 Copyright License

options in a timely manner. Despite a growing number of pioneering algorithms, many of these models have yet to be implemented on a wider scale. While most algorithms are still in earlier stages of development, some AI-ECG models have undergone testing in prospective trials [80, 81]. The current evidence suggests that DL models are more robust and reliable compared to traditional ML approaches [82]. CNN appears to be the dominant method for feature extraction and classification of shockable rhythms [83]. To the best of our knowledge, there is little evidence of a direct comparison between the performance of ML and DL approaches in the detection of shockable ventricular arrhythmias.

In addition to the detection of shockable rhythms, AI can also foster insight into the prediction and management of ventricular arrhythmias. Kabra et al. evaluated the use of RF and logistics regression (LR) in the prediction of VT electric storm events using 37 ECG-based parameters obtained from implantable cardioverter-defibrillator data [84]. Another study proposed a novel hybrid model that could localize the site of VT origin using ECG data [85]. Furthermore, ML can also be applied in ICU heart rhythm alarm systems to detect life-threatening arrhythmias such as VT/VF, extreme bradycardia and asystole. One approach designed an RF classifier that measures ECG, PPG and BP signals to perform heart rhythm classification and can detect the presence of arrhythmia 4 s faster than bedside monitors [86]. Subsequently, this can reduce the number of false alarms and generate a positive impact on patient satisfaction [87].

7.1.7 Limitations of AI

The use of ML and DL approaches can enable healthcare providers to advance individualized care and improve the quality of patient well-being. Nevertheless, the use of AI models in healthcare offers a unique set of limitations that need to be recognized and addressed. Despite the technical advantage of DL algorithms, a large amount of unified data is required to train these models. The availability, standardization and dimensionality of current medical records are impending concerns that need to be addressed before any further proliferation of DL and ML models. Previous literature investigating the use of ML algorithms in CPR rhythm classification suffers from a statistically insignificant number of VT cases in the cohort data [88]. While analyzing the small sample of cases, VT is frequently mislabeled as premature ventricular contractions (PVC) as both arrhythmias are characterized by a wide QRS complex, hence the DL algorithms may confuse the two conditions [89]. Some studies testing for an adaptive filter to remove ECG artefacts utilized an artificial mix of CPR artefacts collected from pigs and clean human ECG data, which reduces the generalizability of data [75]. This notwithstanding, the racial disparities in the prevalence of shockable ventricular rhythms also render the importance of further external validation. For example, a Taiwan registry revealed lower rates of shockable rhythms as the presenting rhythm in OHCA compared to Western databases [90]. As AI training heavily relies on electronic data, this increases the probability of systemic bias. Thus, the lack of a standardized database introduces a major barrier to widespread AI regulation and implementation.

Regarding the "black box" phenomenon, the lack of interpretability of nonlinear features poses a challenge for physicians to decipher the accuracy of the algorithm's outcome. Subsequently, this raises concerns about the legal restrictions and ethical considerations of making a clinical decision. To combat this issue, there is an ongoing debate between constructing simpler DL models with reduced reported accuracy but increased clinical applicability or generating new approaches that aim to validate existing models [91]. For example, Al-Dury et al. compared the factors in predicting survival in patients with shockable and non-shockable VT, and used partial dependence plots (PDP) to elucidate the associations between key predictors and 30-days survival (Fig. 7.5) [63]. The accessibility and cost-effectiveness of AI clinical implementation need to be evaluated. A study found that four commercially available AEDs diagnosed VF almost all correctly, hence one might argue that replacing current methods with AI could drastically increase the complexity and cost with minimal benefit [92]**.** However, the aforementioned study found that VT detection only achieved a moderate level of sensitivity.

Further development of VT detection could be a prospective area of focus in AI development. Firstly, the multimodal biosignals can be analyzed using more advanced preprocessing techniques and algorithm architecture (Fig. 7.3), improving the accuracy and reliability of shockable ventricular arrhythmia detection. Secondly, the explainable AI will play an increasing important role in identifying the pathophysiological factors and mechanisms of shockable ventricular arrhythmia, and providing a more comprehensive evaluation of clinical risks (Fig. 7.5). Finally, multicenter and large-scale datasets can be collected to achieve fine-grained classification in different cohorts, and the investigation of comorbidity with other cardiac and cardiovascular diseases.

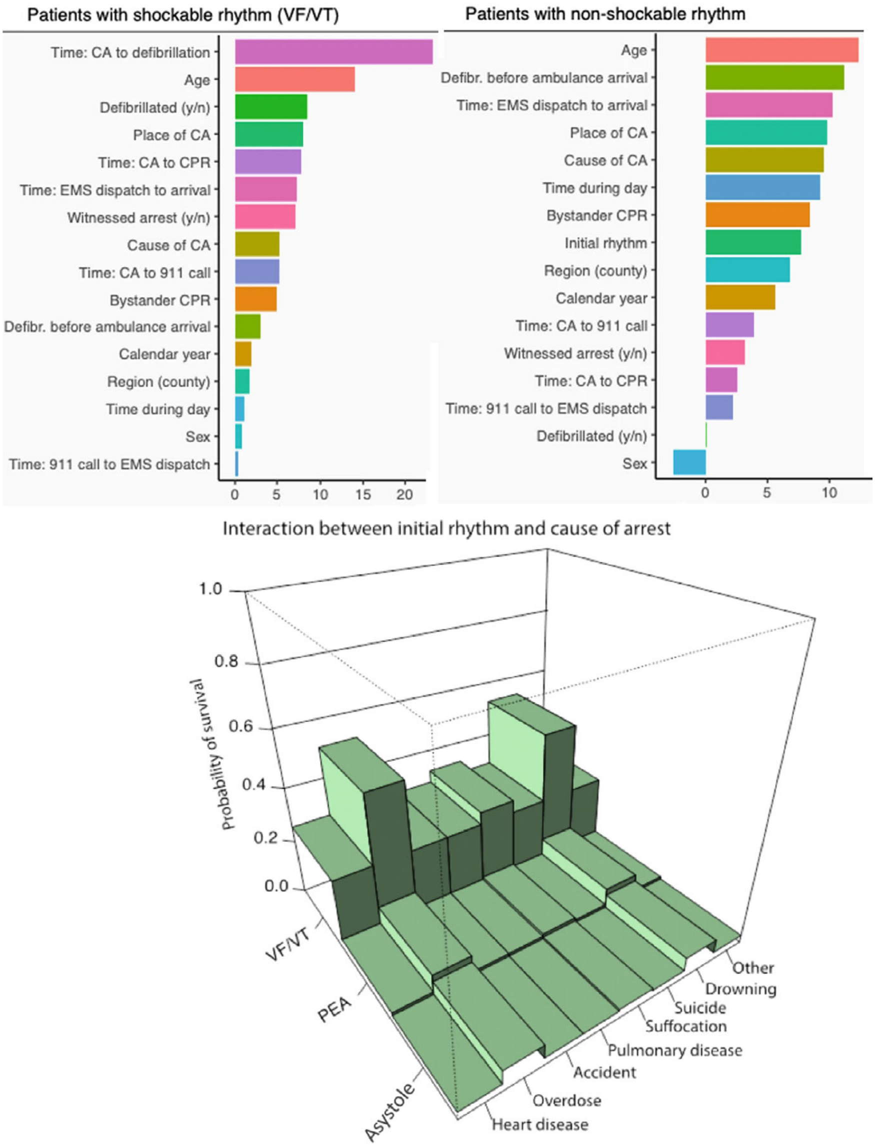

Fig. 7.5 The relative importance of various factors in predicting survival in shockable and non-shockable arrythmias, and the interaction between cause of cardiac arrest and initial rhythm in predicting survival. Reproduced from [63] with permission under CC BY 4.0 Copyright License

7.1.8 Conclusions

This chapter reviewed in detail the performance of ML and DL algorithms for the detection of shockable ventricular arrhythmias using ECG signals, demonstrating moderate to high success for this task. To corroborate, some studies also suggest that the attained sensitivity and accuracy of these algorithms are superior to traditional ECG signal processing approaches. AI-assisted ECG signal processing is likely to expand with time with emerging evidence from ongoing research. Although ML and DL interventions for detecting shockable VA using ECG signals remain in their infancy, many novel AI-based algorithms demonstrate promising potential. Rapid and accurate detection of VT/VF is critical in increasing the survival rate of the patient. The widespread application of AI can expand beyond the detection of shockable rhythms, but it also has the capabilities in resolving many current healthcare challenges. However, a standardized regulatory framework for the clinical implementation of AI remains to be established. It is imperative to recognize the ethical issues and risks involved with AI models in cardiac signal processing.

7.2 Illustrations

See Figs. 7.1, 7.2, 7.3, 7.4 and 7.5.

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Chapter 8
Application of Wearable Sensors in Respiratory Diseases

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Abstract The application of wearable sensors in the medical field has become increasingly prevalent, with a significant impact on the diagnosis of respiratory diseases. The wearable sensors empower real-time monitoring of physiological parameters, including respiratory rate, blood oxygen saturation, blood pressure, and electrocardiogram (ECG) readings, thereby providing physicians with precise diagnostic data. The integration with wireless communication allows for the remote acquisition of patient data by medical professionals, facilitating the practice of telemedicine and health management. Moreover, wearable sensors offer the benefits of portability, comfort, and non-invasive monitoring, making them highly suitable for long-term monitoring and the management of chronic diseases. This chapter overviews the application of wearable devices in the diagnosis of respiratory conditions such as asthma, viral respiratory infections, chronic obstructive pulmonary disease (COPD), and obstructive sleep apnea. It discusses the advantages of these devices, their impact on patient care, and the potential for improving diagnostic accuracy and treatment outcomes in respiratory medicine.

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8.1 Introduction

Wearable sensors are a category of innovative healthcare devices that can be conveniently worn on the body surface, embedded in clothing, attached to the skin, or even implanted within the body. They can not only integrate high portability and real-time functionality but also have extraordinary properties including high biocompatibility for continuous monitoring, user comfort, and integration with healthcare systems. Wearable sensors enable users to collect their own physiological data and get better awareness about their health status [1], which greatly enhances personal health management and quality of life. With application scenarios expanded to multiple diseases, wearable sensors are reshaping the landscape of modern healthcare, paving the way for personalized health management and disease prevention [2].

In last two decades, the micro- and nano-fabrication technologies enable the integration of wireless devices equipped with sensors and transducers into wearable systems towards medical-grade devices. The advanced materials and designs enable wearable sensors to capture subtle signals during the early stages of disease evolution. Various sensors, actuators, infrastructure, medical equipment, various types of intelligent equipment and hospital information systems are connected together via communication network to support data collection, transmission, processing, storage and analysis, materializing the concept of the Internet of Medical Things (IoMT). The passive and continuous monitoring accelerates the accumulation of big health data. Wearable sensors cater for patients in both hospital and home settings and enable healthcare providers for early feedback and data-driven decision making.

Recently, wearable sensors have demonstrated their unique advantages in respiratory diseases during the COVID-19 pandemic. For instance, researchers have developed a COVID-19 diagnostic tool based on paper-based electrochemical biosensors, capable of efficiently detecting targeted antibodies with astonishing sensitivity and specificity of 100% and 90%, respectively, providing strong support for rapid patient screening [3]. By detecting the vital signs and their variability, wearable sensors can comprehensively monitor the physiological status of patients with respiratory diseases. These data provide important reference for data-driven healthcare especially for chronic respiratory diseases. In this chapter, we comprehensively review the technical advancements in wearable sensors and their applications in respiratory disease. We summarize the advantages, limitations, and challenges to provide reference for researchers, healthcare providers, and biomedical engineers.

8.2 Types of Wearable Sensors for Respiratory Monitoring

There are some key physiological parameters relevant to respiratory healthcare (Fig. 8.1). Researchers have developed different types of wearable sensors using different mechanisms to measure these parameters.

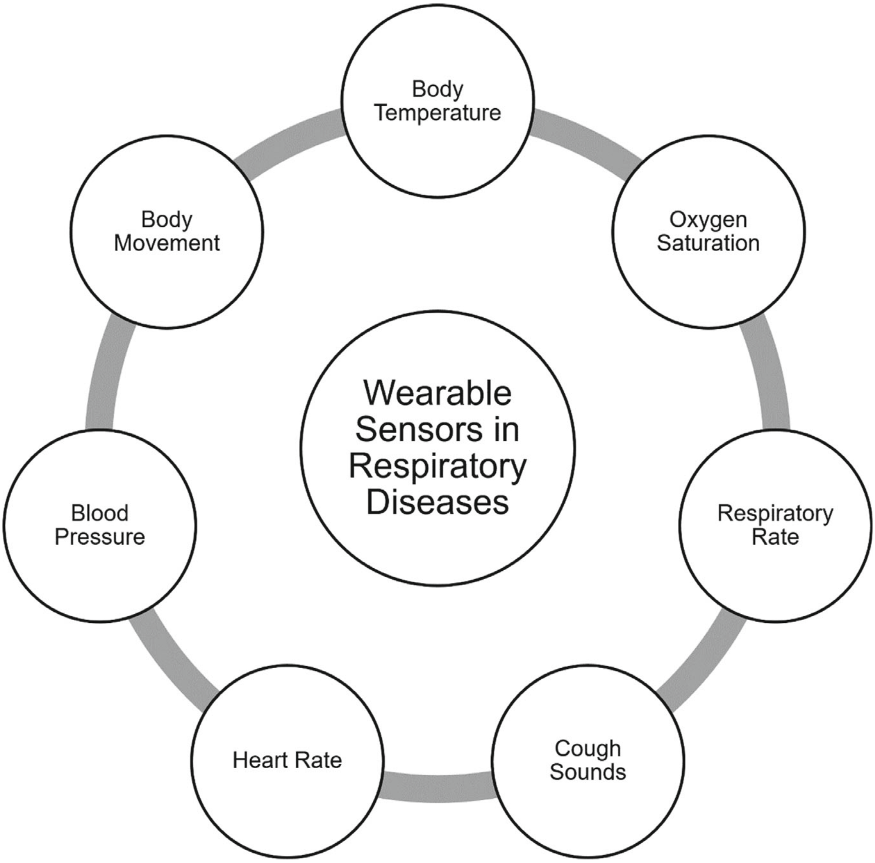

Fig. 8.1 Different parameters from wearable sensors in respiratory monitoring

8.2.1 Temperature Sensors

Fever is common symptom of many respiratory diseases and can be used for early diagnosis and assessment. Many wearable devices have been developed for quick and accurate measurement of body temperature. For example, TempTraq is a soft, skin-friendly, and comfortable patch sensor for infants and young children that can continuously measure body temperature for up to 48 h [4]. It synchronizes real-time data to a smartphone application via Bluetooth technology, allowing parents to monitor the child's health status and take timely actions. The Oura smart ring is multi-functional wearable device [5] for body temperature measurement, step tracking, and heart rate monitoring. The Oura smart ring incorporates a long-lasting battery that can last up to seven days, thereby reducing the hassle of frequent charging. Additionally, its waterproof feature and a lightweight design of only 7 g ensure user comfort. Users can connect it to a mobile application via Bluetooth to check their health metrics, achieving intelligent and personalized health management. The VivaLNK Fever Scout [6] is a wireless thermometer patch specifically designed for fever monitoring. With its skin-adhesive patch design, it can accurately capture changes in body temperature and transmit data wirelessly to a companion device or application. This design not only enhances the accuracy of skin temperature measurement and enable early detection of fever in different application scenarios. These advanced wearable devices provided strong support for the early and accurate detection of fever in infectious respiratory diseases and serious symptoms.

8.2.2 Pulse Oximetry Sensors

A key function of circulatory system is the delivery of oxygen to different parts of the body via the hemoglobin. A state of hypoxia, where the blood oxygen saturation (SpO_2) falls below the normal level, especially when this value drops below 95%, can lead to serious health consequences, including but not limited to brain function impairment, heart failure, and even sudden death [7]. In this context, accurately and continuously monitoring SpO_2 holds invaluable significance for preventing severe clinical events.

The key technology in mainstream wearable pulse oximetry sensors is photoplethysmograms (PPG) which detects volumetric changes in microcirculation. Based on the different absorption characteristics of oxygenated and deoxygenated hemoglobin to specific wavelengths of light, SpO_2 can be calculated from multi-wavelength PPG signals. The regions with rich blood circulation such as the fingers, toes, and earlobes, can be used for PPG signal measurement. Fingertip is most widely used measurement site in pulse oximetry sensors due to its convenience for operation and high signal quality [8–10]. An innovative design of battery-free, miniaturized, and nail-style pulse oximeter with wireless communication is proposed which enhanced the comfort of wear for users but and improves the portability [11].

The desired features for pulse oximetry sensors include long-term monitoring, extended battery life, the reusability of the device, and multimodal data analysis for symptom detection. These features reflect market demand for next-generation wearable pulse oximetry sensors that are durable, economical, and capable for home-based monitoring, with the ability to analyze multiple physiological parameters simultaneously.

8.2.3 Respiratory Rate

Respiratory rate (RR) is a vital sign that often serves as one of the key indicators in assessing an individual’s health status and the progression of diseases. In the clinical assessment of respiratory system diseases, RR, along with SpO_2, heart rate (HR), and body temperature, forms a critical set of clinical features for evaluating the severity of conditions. Specifically, for patients experiencing severe respiratory distress, if their RR remains above 30 breaths per minute, it may indicate a significantly increased risk of developing the serious complication of acute respiratory distress syndrome (ARDS), a viewpoint that has been widely confirmed in numerous studies [12, 13].

Many wearable sensors have been developed RR measurement based on thermal, acoustic, mechanical, and chemical changes during respiration [14]. Advanced technologies such as strain gauge sensors, triboelectric sensors, and accelerometers have been deeply studied and applied to monitor chest or abdominal volume changes caused by respiratory movements, thereby achieving accurate measurement of RR [15, 16]. RR can be extracted from other physiological signals using demodulation [17, 18]. By integrating these sensors into chest belts [16, 19] or directly affixing them to the skin surface [20], several convenient, comfortable, and efficient wearable RR monitoring products have been developed, such as RespiraSense [21] and innovative devices based on the principle of dermal thermal sensing [20]. The emergence of these products not only greatly enhances the convenience and accuracy of RR monitoring but also provides strong technical support for the early detection, timely intervention, and effective management of respiratory system diseases and other related health conditions.

8.2.4 Cough and Respiratory Sounds

Cough monitoring plays a key role in timely detection of severe symptoms, early diagnosis of diseases, and precise assessment of disease progression. The cough signals are derivable through two approaches. First, audio sensors, such as wearable microphones, can capture the distinct audio characteristics of cough sounds. Second, mechanical sensors, especially piezoelectric transducers and high-sensitivity accelerometers placed in the throat or chest area [22–24], can detect the subtle vibrations caused by cough movements, thereby achieving comprehensive monitoring of cough behavior.

To improve the performance of cough detection, researchers have proposed advanced audio signal processing technologies, pattern recognition methods, and machine learning (ML) classification algorithms. These algorithms, with large-scale cough audio data for training, can automatically recognize and distinguish different types of cough sounds, providing strong support for clinical decision-making [23].

Additionally, auscultation of the lungs, an indispensable part of respiratory system disease examination, traditionally requires the involvement of a professional and is limited by the direct contact between the stethoscope and the body. To overcome this limitation, a research team has proposed a wearable stethoscope patch solution. This patch integrates MEMS stethoscopes, ambient noise sensors, electrocardiogram, impedance pneumography analysis, and a nine-axis activity logger, to achieve comprehensive monitoring of respiratory sounds, cardiac activity, lung impedance changes, and body movement [25, 26]. This system allows for continuous auscultation and captures subtle pathological changes such as wheezing and abnormal breathing sounds, providing a new technical means for the early diagnosis and assessment of respiratory system diseases.

8.2.5 Electrocardiogram

Electrocardiogram (ECG) serves as a vital diagnostic tool for cardio-respiratory diseases. Remote ECG monitoring systems based on wearable devices are emerging, which inherits the core functions of ECG monitoring and reduces the risk of cross-infection by minimizing direct contact between healthcare providers and patients.

Adhesive ECG patch is a most common approach for wearable ECG monitoring. A ECG patch device usually contains a sensor system, microelectronic circuits (with built-in recorders and memory), and high-energy internal embedded batteries, forming a compact wireless monitoring unit. The miniaturized design increases users' comfort during continuous recording of ECG data for extended periods (even multiple days), providing doctors with abundant diagnostic information. Taking the MCOT patch as an example [27] (manufactured by BioTelemetry, located in Malvern, Pennsylvania, USA), it has been successfully applied in monitoring the ECG changes of patients undergoing treatment with hydroxychloroquine and azithromycin, demonstrating its significant potential in clinical practice. In addition, the market has seen the emergence of several ECG patch products with similar functionalities, such as the Savvy Monitor (originating from Ljubljana, Slovenia) [28] and the VitalPatch wearable sensor designed, developed, and launched by Corventis in San Jose, California, USA (now operated by VitalConnect) [29]. These products have propelled the rapid development of wearable ECG monitoring technology, providing patients with a more convenient and efficient medical service experience.

8.2.6 Monitoring Blood Pressure

Blood Pressure (BP) is a vital sign that reflects the health status of the cardiovascular systems. Continuous, remote, and real-time monitoring of blood pressure is not only conducive to timely warning of potential cardiovascular emergencies for the patients with severe respiratory symptoms.

A variety of wearable devices for BP monitoring have been proposed including watches [30], smart glasses [31], patches [32], as well as high-tech shirts [33] and wearable skin-like tattoo sensors [34]. These devices achieve non-invasive continuous tracking of blood pressure, while there are some unmet challenges for high precision and long-term stable monitoring. Particularly when tracking the effects of medication on blood pressure, ensuring the accuracy of data without frequent calibration has become an urgent issue to be resolved, considering the complex dynamics of BP fluctuation and its variability among individuals.

To address this challenge, researchers have proposed a pressure detection system that combines wearable devices with deep learning algorithms [35]. In this study, the research team recruited 212 medical personnel as subjects, using a variety of wearable devices such as Fitbit smartwatches, smartphones, smart bras (OMSignal), recorders (TAR), and location tracking devices (Owl-in-one) to continuously collect physiological data from the subjects over a period of 10 weeks. Subsequently, a Long Short-Term Memory (LSTM) deep neural network was employed to detect individual stress levels. It is worth noting that while this method has shown good performance in daytime stress monitoring, its effectiveness for special groups working at night may be affected to some extent. In the future, with the continuous advancement of technology, researchers are expected to incorporate more physiological characteristics into the monitoring scope, further enhancing the comprehensiveness and accuracy of the system, and bringing revolutionary changes to the field of blood pressure management and overall health management.

8.3 Application of Wearable Sensors in Different Respiratory Diseases

The wearable sensor plays a key role in the IoMT-based respiratory healthcare monitoring (Fig. 8.2). The sensors will collect different types of signals and parameters from the patients in different application scenarios (hospital and home monitoring). The data will be uploaded to the cloud for advanced signal processing to support clinical decision-making, with early feedback from clinicians.

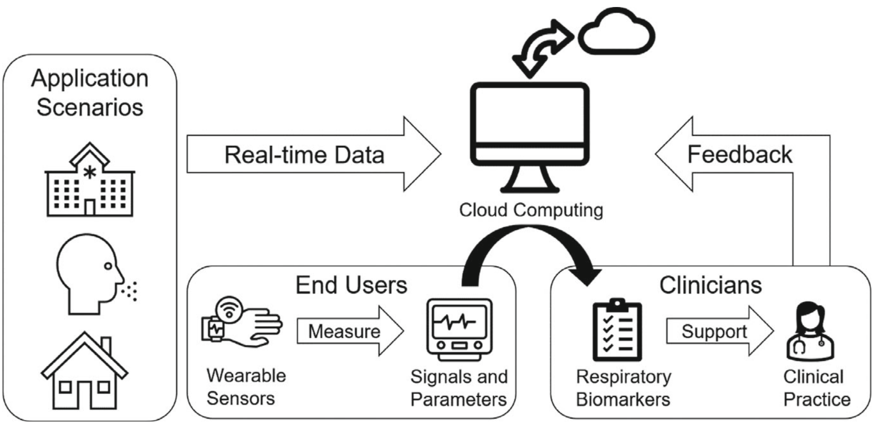

Fig. 8.2 Application of wearable sensors in respiratory healthcare, icons from Microsoft Powerpoint and flaticon.com under free license

8.3.1 Application in Asthma

Asthma affects 8–9% of the US population, especially affecting people with lower income [36], this not only leads to a heavy medical economic burden but also results in thousands of preventable tragic deaths. Although existing asthma treatment guidelines emphasize the assessment of lung function through objective means like spirometry (such as FEV1, PEF, FVC, etc.), these professional tests are often not readily available during acute asthma exacerbations, as patients are not usually in medical institutions equipped with standard spirometers.

Environmental factors are often overlooked in the management strategies for chronic diseases, as exemplified by the current state of management of asthma. The environmental factors, such as exposure to pollutants and cold, dry air, are significant triggers for acute asthma exacerbations, and their effects are often delayed following exposure, lasting from several hours to days. Epidemiological studies have clearly established a close link between ozone exposure and the deterioration of lung function in asthma patients [37]. Therefore, achieving long-term monitoring of lung function in asthma patients, combined with information on their local environmental exposures, is of great significance for identifying individual sensitivities to environmental stressors, timely adjusting treatment plans, and preventing adverse outcomes.

Several solutions have been proposed to address this unmet need, encompassing real-time monitoring of HR and RR [38], using GPS to track exposure to polluted areas [39] and early-stage consumer products for tracking physiological parameters [38]. Among them, the wrist-worn Asthma Research Tool ("ART") is a promising one. This device integrates commercial off-the-shelf (COTS) components at a low cost (below $150) and can automatically record users' ozone, total volatile organic compounds (TVOC), temperature, humidity, and activity level data every minute. These data can be stored locally in built-in flash memory or transmitted to a central database via a Bluetooth module, providing comprehensive and real-time information support for clinical decision-making. With a detection limit of 10 ppb and the 60 ppb threshold for pulmonary inflammation in healthy individuals set by the U.S. Environmental Protection Agency (EPA), ART has the capability to measure ozone exposure that has therapeutic significance [40], offering asthma patients a more personalized and precise health management plan.

8.3.2 Application in Viral Respiratory Tract Infections (VRTI)

Viral Respiratory Tract Infections (VRTI) are common. In the United States, it is estimated that annual influenza epidemics result in the loss of approximately 610,660 life years and incur an economic cost as high as 87.1 billion dollars [41]. In Canada, the annual flu season leads to an average of 12,200 hospitalizations and results in the unfortunate deaths of about 3500 people [42]. The early detection VRTI in the asymptomatic phase is important to alleviate the strain on the healthcare system and curb potential future pandemics, where wearable sensors are an increasingly important role.

A forward-looking controlled longitudinal study conducted in 2023, known as the "WE SENSE study," has demonstrated an innovative detection method that leverages a broad array of multimodal physiological biosensors. This method is based on changes in the circulating levels of objective biomarkers of the immune host response, through the simulation of low-grade viral attacks and continuous monitoring with wearable biosensors over a 12-day period. It has opened up new avenues for the identification of asymptomatic or mildly symptomatic VRTI [43]. The wearable sensors can continuously, dynamically, remotely, and non-invasively monitor physiological indicators, which ensures the safety of healthcare workers, saves medical resources, and brings in convenience for patients, as demonstrated during COVID-19 pandemics.

8.3.3 Application in Chronic Obstructive Pulmonary Disease (COPD)

COPD is the third leading cause of death worldwide, characterized not only by its severe impairment of lung function but also by the presence of multiple comorbidities [44]. Physical function is an important measure of an individual's ability to perform daily and complex physical activities, and is valuable for assessment health status and predicting the risk of disability [45–47]. Reduced physical function is closely related to the progression of chronic diseases, including but not limited to COPD [48–50].

In the clinical assessment of COPD patients, physical capacity is traditionally quantified through functional tests such as maximal oxygen uptake tests or the 6-Minute Walk Test (6MWT) [51]. To capture the real-world activity in patients' daily lives, validated questionnaires are often used to collect self-reported data [52, 53]. Wearable devices can continuously and objectively monitor various aspects of physical function in a free-living environment [54–57], offering a new approach to addressing the limitations of traditional clinical tests in terms of real-time monitoring, continuity, and ecological validity [58]. This is particularly significant for chronic diseases like COPD whose symptoms are easily influenced by medications and environmental factors [59–61].

In recent years, physical fitness tests such as the 6-Minute Walk Test (6MWT) and the Timed Up and Go (TUG) test have gradually been introduced into the home environment for the assessment of patients with cardiovascular, pulmonary, and neurological diseases [62–64]. These tests, aided by modern wearable sensors and smartphone applications, have achieved precise measurement of key parameters like walking distance and test completion time [55, 65–67], proving to be more convenient and efficient than traditional methods of using ropes and stopwatches

[68, 69]. The 6MWT and TUG tests assisted by wearable devices can reliably assess the physical condition of COPD patients in both clinical and home settings [70]. This approach helps to evaluate patients' physical capabilities in real-life settings and provides evidence for personalized treatment plans towards effective disease management.

8.3.4 Application in Obstructive Sleep Apnea (OSA)

Obstructive Sleep Apnea (OSA) is a prevalent sleep disorder characterized by recurrent episodes of upper airway obstruction during sleep. Previous studies have clearly revealed the association of OSA with a range of serious health issues, including but not limited to heart disease [71], type 2 diabetes [72], stroke [73], and depression [74]. These findings underscore the profound impact of OSA on an individual's overall health, quality of life, and work efficiency. As the gold standard for assessing OSA, polysomnography (PSG) provides comprehensive diagnostic evidence by continuously monitoring various physiological parameters (such as EEG, nasal and oral airflow, chest and abdominal movements, and snoring) during an 8-h sleep period in a hospital setting. However, given the complexity and cost of PSG, it is particularly important to explore more convenient and economical alternative assessment methods.

Against this backdrop, out-of-center testing options such as Home Sleep Testing (HST) and Home Sleep Apnea Testing (HSAT) have emerged. They not only allow patients to complete assessments in the comfort of their own homes but also promote the optimal allocation of medical resources and enhanced patient-physician interaction. HSAT integrates cutting-edge technologies such as wearable devices, artificial intelligence, intelligent medical history analysis, remote medical services, and big data aggregation [75]. This has improved the convenience and precision for the diagnosis of OSA.

SensEcho is a wearable multi-sensor system for HSAT. The system comprehensively monitors sleep states by automatically analyzing audio recordings, capturing single-lead ECG signals, chest and abdominal movements, and integrating 3-axis accelerometers with finger pulse oximeters to monitor posture and blood oxygen levels. It employs a bidirectional long short-term memory (BLSTM) network algorithm that can accurately distinguish between sleep and wake states and precisely delineate various stages of sleep (light sleep, deep sleep, rapid eye movement [REM], and wakefulness), showing a high degree of consistency with manual PSG analysis results [76]. Notably, the unique design of SensEcho—a sleep monitoring vest—completely abandons the need for head and leg electrodes and nasal airflow tubes required by traditional PSG, reducing interference with the patient's sleep and promoting a more natural sleep state. Its simple setup process enables home self-testing and outpatient diagnosis. In addition, it can be worn continuously for over a week, providing strong support for long-term monitoring of sleep rhythm patterns [77, 78] for comprehensive evaluation of OSA.

8.4 Challenges and Prospects of Wearable Sensors in the Diagnosis of Respiratory System Diseases

The signal quality of wearable sensors often depends on the measurement status. Especially, the PPG and accelerometer signals can be noisy during body movement, making it difficult to extract respiratory movement [79, 80]. As a result, the utility of wearable devices at the clinical level is still limited due to the lack of validation. This issue can be addressed through commitments to clinical trials from both the government and individuals. In addition, the real-time signal processing is challenging, leading to the delay and difficulties in building IoMT. The real-time data analysis and communication also reduce the time required for patients to get feedback or intervention especially in emergent cases. Considering the inconsistency in data quality, and the possible risks caused by false results, currently the wearable sensors should be replaced clinical staffs. The improvement in materials and sensor design can improve the signal quality and the reliability of measurement results. The data privacy and security are another challenge. It needs comprehensive efforts in encryption algorithms, access control, ethnical review, and management. Data collection and storage are typically determined by the user. Therefore, the user-defined security issues need further clarification. Wearable devices should be compact, easy to use, and biocompatible to minimize the impact on patients' daily activities. There is a gap in high-quality research on user preference in real-world settings. Related issues such as device battery life and safety concerns also need to be addressed. Finally, the existing wearable devices, such as fitness trackers, smartwatches, and smart helmets, only follow one or a few related symptoms. The comprehensive diagnosis of different respiratory diseases and their comorbidities warrants further investigation.

8.5 Conclusion

With the rapid advancement of technology, the application of wearable devices in the medical field is increasingly widespread, with great potential in the diagnosis of respiratory diseases. These devices are lightweight and portable, enabling patient's self-management and monitoring in daily settings. By continuously monitoring and analyzing these data, wearable sensors can empower clinicians to make early diagnosis and personalized treatment plans.

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Chapter 9
Low-Cost Wearable Sensors for Monitoring Sleep: A Review of Recent Developments and Applications

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Abstract Recent advances in wearable sensor technology have thus opened up new, cost-effective strategies beyond sleep monitoring. This review paper discusses developing new applications of wearable, low-cost sensors in sleep monitoring. This paper tries to provide a detailed review of all sensed modalities—accelerometer, photoplethysmography, and temperature sensors, and how they can be combined to maximize their role in capturing sleep metrics, such as sleep stages, heart rate variability, and respiratory patterns. The paper also foresees the adoption of these sensors in wearable devices and their impact on healthcare shortly about early detection and individual sleep management strategies. Lastly, challenges and future research directions are discussed regarding the subject area of low-cost wearable sensors in sleep monitoring, which gives insights into how to improve accuracy, reliability, and accessibility for researchers and developers of such technologies.

Keywords Wearable-sensor technology · Sleep monitoring · Wearable devices · Sleep management strategies

9.1 Introduction

Sleep is an aspect of good health that helps one feel better, and concentrate, and generally impinges on the entire physiological and psychological condition of man. Adequate sleep has been related to good performance, emotional control, and overall well-being, while sleep disturbances have been reported to be associated with a wide range of health problems, including cardiovascular diseases, obesity, diabetes, and neurological and psychiatric disorders [1, p. 2]. Despite this fact, sleep disorders mostly go unacknowledged because convenient and accessible monitoring tools are lacking. On the other side, traditional sleep analysis methods, such as PSG, provide

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extensive sleep data that is very expensive, cumbersome, and restricted to clinical settings, making it impracticable for widespread use [3, p. 2].

Wearable low-cost sensors have opened up a new frontier in the study and monitoring of sleep, allowing monitoring by individuals in the convenience of their homes. Devices that can be worn on the wrist, head, or even embedded in clothes use different sensors to measure physiological variables such as heart rate, movement, skin temperature, and electrodermal activity. These metrics allow the estimation of stages of sleep, and detection of interruptions, and hence provide insights into overall sleep quality when using wearable sensors [4, p. 68].

Sensor technology[1] has evolved significantly in the miniaturization of the equipment and also machine learning algorithms that extend its functionalities and further increase its accuracy. In turn, pending development in wireless communication and battery life is expected to even further enhance wearability and provide for their application in continuous monitoring for a longer time than originally possible [5, p. 19019]. Besides, accumulation on cloud-based platforms of data and its further analysis enable immediate feedback and personalized recommendations; thus, such devices are not only tracking sleep but also a means for better sleep hygiene and a tool for the management of sleep disorders.

This review comprehensively covers recent advancements in the field of low-cost wearable sensors used for sleep monitoring. Variations of sensor types that may be used within these devices are discussed, including but not limited to accelerometers, photoplethysmography, and electroencephalography with respective strengths and weaknesses [2, p. 47]. The applications of these wearable sleep sensors in various fields, both clinical and non-clinical, will also be reviewed, including roles in research, diagnosis of sleep disorders, and consumer health. Other challenges identified with these technologies include data accuracy, privacy concerns, and user compliance. Sensor technology, advanced data analytics, and health solutions at a personalized level may still see full-scale and complete innovations. In light of these views, the review might go further to say that low-cost wearable sensors could devise innovative ways to monitor sleep and thus help improve the understanding of health in sleep on a global scale [6, p. 162].

9.2 Brief Discussion

Wearable, low-cost sensors have enabled sleep monitoring from new angles and at significantly reduced costs compared to conventional approaches such as PSG. Wearable technologies have rapidly developed from rather simple devices into highly sophisticated devices, often integrating advanced sensor technologies with complex

[1] Sensor technology involves designing and using devices for the detection and measurement of variables of physical, chemical, or biological nature by converting such measurements into signals that are interpretable or recordable. Sensors have been developed to respond to an ambient environmental stimulus-more often than not, temperature, pressure, light, motion, or chemical composition-and convert them into readable outputs many times electrical in form.

data processing algorithms to extract meaningful information from sleep patterns. The presented review discusses recent advances in sleep-monitoring technologies based on wearables and their applications, along with the challenges arising from such approaches.

9.3 Ongoing Developments in Wearable Sensors of Sleep

Low-budget, wearable sensors can often enable multiple sensors that capture various types of physiological and behavioural data related to sleep.

An accelerometer commonly serves the purpose of measuring motion, and thus finds extensive relevance in stages of sleep identification and other forms of sleep disturbances, such as restless movements. Accelerometers can deduce periods of wakefulness and sleep by analyzing the pattern of movements, thus providing information about sleep duration and quality [7, p. 84].

Photoplethysmography: PPG sensors work by employing light-based technologies to measure changes in blood volume in the microvascular bed of tissue. This enables heart rate and HRV to be monitored, which are two key indicators of sleep stages. Recent technologically improved PPG advances have optimized its accuracy with simultaneous power consumption reductions that enable continuous overnight use [8, p. 62].

EEG: Traditionally part of PSG, the sensors have recently been miniaturized for wearables. It is a device that measures electrical activity in the brain and is considered to be the gold standard for distinguishing between the different stages of sleep, like REM and non-REM sleep. Wearable EEG systems, although much less comprehensive compared to clinical ones, have become more accurate and more comfortable, so they are well-suited for everyday use [1, pp. 4–5].

EDA Sensors: These sensors detect skin conductance that usually varies with sweat gland activity. Since the EDA is under the influence of the autonomic nervous system itself, it may help with insight into stress levels and states of arousal, which are relevant to understanding quality sleep and sleep disruptions [2, p. 48].

9.4 Sleep Monitoring Applications

Wearable sleep sensors are considered relatively inexpensive and have various applications beyond simple consumer-based sleep tracking. More recently, such devices are finding increased application in clinical research, the diagnosis of sleep disorders, and the elaboration of personalized health interventions [3, p. 4].

Consumer Health and Wellness: Wearable sensors have gained widespread interest among individuals looking to enhance the quality of their sleep. Wearable devices like smartwatches or fitness bands make detailed daily reports on sleep duration, efficiency, and disturbances present to the user. It is with such reports that one may be able to establish trends and institute changes in sleeping behaviour. Some of the sensors go further to suggest actions that the user should engage in, based on real-time feedback from data collected, thereby fostering good habits for sleeping [4, pp. 69–70].

Wearable sensors have become an indispensable tool in sleep research, enabling large-scale studies in naturalistic settings. The relative affordability and ease of use of devices mean that as a rule, voluminous data from large and varied populations over long periods can be collected by researchers while looking precisely at how sleep affects health and behaviour. Wearables have thus been used to study how sleep influences cognitive performance, mood, and the course of chronic diseases [5, p. 19022].

Diagnosis and management of sleep disorders: Wearable sensors are increasingly being explored for diagnosis and management of sleep disorders like insomnia, sleep apnea, and restless leg syndrome. While these devices have not yet replaced PSG, they offer a much less invasive alternative and allow for easier access to preliminary screenings. For example, some wearables can detect apnea events by recognizing breathing and heart rate patterns. This will, in turn, help in highlighting the individuals who further need evaluation with PSG and thus help in streamlining the diagnostic process [6, pp. 164–165].

Wearable Sensors for Remote Patient Monitoring[2]: Wearable sensors in health care can have the potential to remote-monitor patients with sleep disorder or any disease course that has a negative consequence on sleep [8, p. 66]. Continuous monitoring will enable the provider to track treatment progress and allow real-time interventions with more personalized care. This has been highly applicable during the integration of wearable sensors into the telemedicine platform in this regard, where visits cannot be made face-to-face during the COVID-19 pandemic [7, p. 87].

9.5 Limitations and Difficulties

Large issues pertain to accuracy: the different types of data that can be acquired through wearable sensors. While these have considerably improved, they can't replace the precision of clinical PSG, especially for sleep stage discrimination [3, p. 3]. Sensor placement, user movement, and other environmental factors would contribute further toward the variability in data quality. Most of the work has focused on the validation of data from sensors against PSG and other measures to make these data more reliable [5, p. 19024].

User Compliance and Comfort: It will be important that wearable sensors are unobtrusive and easy to use. Poor user compliance could be due to the inconvenience

[2] RPM represents a health practice involving the utilization of digital technologies in the collection of medical and health-related data from patients from one location, which is transmitted in electronic form to health care providers from another, different location. This model enables healthcare providers to monitor patients' conditions for the management of chronic diseases outside the four walls of hospitals and physician clinics-more often within the comfort of the patient's home.

created either by the device itself or by many sensors on the body. Ensuring that devices are unobtrusive and do not interfere with sleep is critical to their widespread adoption. Moreover, the long-term wearability and battery life will influence user experience [3, p. 5].

Privacy and Security: The continuous collection and transmission of personal health data raise concerns about privacy and security. Wearable devices will be bound by high standards about the safeguarding of data so that any sensitive information belonging to users will not be leaked or disclosed. Besides, the strong encryption and anonymization features that are necessary for the protection against unauthorized access and breaches should be provided by the manufacturers and the developers [4, p. 3].

Integration with Health Care Systems: If wearable sensors are to find broad use in practice, there is a great need for integration into healthcare systems at the levels of collection, analysis, and interpretation using standardized protocols. This would eventually allow for their incorporation into EHRs and enable healthcare providers to adopt their use in clinical decision-making [6, pp. 168–169]. However, such attainment requires collaboration between device manufacturers, healthcare providers, and regulatory bodies.

9.6 Prospects and Opportunities in Future

Future sensors will also be developed with advanced materials and technologies, such as flexible and stretchable electronics that improve comfort and signal quality. The development of multimodal sensors that monitor more than one physiological parameter simultaneously could help provide a more complete understanding of sleep health [7, pp. 89–90].

The advanced sensor technology may include novel materials and technologies such as urethane-based resin, and flexible, and stretchable electronics that increase comfort and accuracy. Multimodal sensor development can create a picture of sleep health on multiple axes by monitoring several physiological parameters at once [1, p. 25].

Artificial Intelligence and Machine Learning: These are bound to feature more in the development of improved sleep data analysis. AI, but more so machine learning, opens up huge possibilities for a more accurate and personalized interpretation of sensor data, hence even better insights and recommendations for the user [1, p. 32]. Advanced sensor capabilities in the future will enable personalized health interventions in sleep. These include customised intervention into the individual's particular sleep patterns and needs, including customised conduct of sleep hygiene, advanced scheduling of sleep, and symptomatic therapies for sleep disorders [8, p. 70].

Wearable sleep sensors, through devices and other systems, integrate into health monitoring purposes for an integrative approach to health management. In this regard, it may involve sleep information integrated with input data from fitness trackers, dietary logs, and mental health apps for complete insight into the general well-being of a particular individual [1, pp. 9–10].

Regulatory Issues: As wearable sensors become increasingly integrated into health care, there will be an increased need to clearly outline their regulatory issues in the interest of safety and effectiveness. Ethical Issues: Data privacy and over-reliance on technology give rise to ethical issues [1, p. 16].

9.7 Conclusion

Low-cost, wearable sensors for sleep monitoring are among the most significant latest advances in healthcare and consumer technology. These devices have increased access to sleep tracking among the general population and have enabled easy and convenient sleep pattern monitoring [3, p. 7]. From simple fitness gadgets, the study of wearable sleep sensors has evolved to become a sophisticated tool, leveraging advances in sensor technology, data analytics, and wireless communication to enable detailed insights on quality, duration, and disturbances in sleep. However, they do much more than that for personal health management. Clinically speaking, they offer a scalable approach for initial sleep disorder screening, remote monitoring of patients, and large-scale sleep studies [2, p. 50]. This accessibility has the potential to bridge the gap between clinical sleep studies and everyday health monitoring, allowing for earlier detection and intervention of health issues related to sleep.

Nevertheless, despite all their promises, various technologies continue to suffer from important challenges. For example, the accuracy of wearable sensors is still not comparable to the gold standard, namely polysomnography, though the accuracy continues to improve. This has been one of the main concerns regarding the reliability of such devices in clinical settings where precise identification of stages of sleep is quite crucial [7, pp. 92–93]. Apart from these, user compliance is another major factor that could affect the effectiveness of such devices. The comfort and ease of use with a minimum level of intrusiveness is a challenge from the design point of view due to the high demand for wearable sensors [4, p. 79].

Then, there is also data privacy and security. Since these are devices collecting very sensitive information about a person's health, this area should be strongly secured in terms of data storage and transmission. Certainly, it has to be important that the ethical consequence of continuous health monitoring is taken into consideration-particularly about ownership of data and consent issues [6, p. 171].

Whereas much has been done, there is yet to come in the development of wearable sleep sensors from the integration of artificial intelligence and machine learning to new wearable devices that will improve wearables' functionality [4, pp. 83–84]. With new wearables supported with these technologies, they could potentially interpret more from the data, provide personalized recommendations, and even predictive analytics that might enable people to avoid potential sleep disruptions. More generally, the future of wearable sleep monitoring may comprise deeper integrations of sleep data with larger health ecosystems [3, pp. 8–9].

Low-cost, wearable sensors for sleep monitoring are at the leading edge of a technological revolution in sleep health. If fully developed, they could make monitoring sleep a routine part of personal health management and greatly improve the diagnosis and treatment of sleep disorders [4, p. 89]. Yet, if this potential is to be realized, challenges concerning accuracy, user experience, privacy, and healthcare integration will require continued effort. With further development of these devices over the coming years, there may be a chance that they could be better positioned to play an increasingly critical role in supporting both better sleep and health in heterogeneous populations.

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Chapter 10
An IoT-Enabled Time-Frequency Domain Ensemble Deep Learning Framework for Detection of Pulmonary Diseases Using Lung Sound Recordings

Rishabh Mittal, Harshit Juneja, Nagajyothi Kasimkota, Rajesh Kumar Tripathy, and Ram Bilas Pachori

Abstract Pulmonary diseases (PMDs) are abnormalities affecting the lungs and respiratory system. The lung sound recording offers a non-invasive and cost-effective modality for early diagnosis and monitoring of these diseases. The automated detection of PMDs from lung sound signals using artificial intelligence (AI) techniques is crucial for early detection and helps improve patient outcomes by reducing healthcare costs. In this chapter, a novel ensemble deep neural network (EDNN) model deployed on an Internet of things (IoT)-enabled web application (WAAP)-based framework is proposed for automated detection of PMDs such as pneumonia (P), chronic obstructive pulmonary disease (C), and asthma (A) using time-frequency domain (TFD) representation of lung sound recordings. The short-time Fourier transform (STFT) obtains the TFD representation from the lung sound signal. The TFD image of the lung sound signal is given as the input to the EDNN model for the automated detection of different PMDs. The performance of the proposed EDNN approach is evaluated using lung sound recordings of different subjects from a public database. The results show that the proposed EDNN approach has obtained overall accuracy values of 87.61% and 90.23% for four-class (normal (N) vs. A vs. C vs. P) and three-class (N vs. A vs. P) schemes. The suggested approach has demonstrated a higher accuracy than the existing methods to detect multiclass PMDs using lung sound recordings. The proposed IoT-enabled TFD-based EDNN approach can be investigated using

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lung sound data from a wearable microphone-based sensing device for automated detection of PMDs.

Keywords Pulmonary diseases · Lung sound · Ensemble deep learning · Accuracy · Web application · IoT

10.1 Introduction

Pulmonary diseases (PMDs) such as asthma, pneumonia, and chronic obstructive pulmonary disease (COPD) significantly affect breathing and the overall health of a person [1]. Asthma is a chronic respiratory condition characterized by narrowing of airways and inflammation [2]. The significant asthma symptoms are coughing, chest tightness, shortness of breath, and wheezing. Similarly, COPD is a progressive PMD that causes obstructive airflow from the lungs, making breathing difficult for the person [3]. The symptoms of COPD are excess mucus formation, chronic cough, and shortness of breath. Smoking is the primary cause of COPD, and it accelerates COPD progression and exacerbates the symptoms of asthma [4]. Pneumonia is a lung infection caused by viruses and bacteria [5]. The symptoms of pneumonia are difficulty in breathing, cough, and fever. The lung sound recording is a diagnostic modality used to capture the sound produced by air movement through the respiratory system [1]. A stethoscope is typically used for the recording, and the graphical representation of the recorded audio data with respect to time is interpreted as the lung sound signal. This signal captures the normal (tracheal, vesicular, bronchial, and bronchovesicular sounds) and abnormal sounds such as wheezes, rhonchi, stridor, and crackles [6]. Lung sound recording is a non-invasive procedure, and it is more cost-effective than imaging modalities such as X-rays and CT scans for diagnosing PMDs [7]. It is beneficial for initial assessment and primary diagnosis of PMDs. However, for comprehensive evaluation of PMDs, imaging modalities such as chest X-rays and computed tomography (CT) scans are typically used in clinical studies [8]. The automated system uses artificial intelligence (machine learning (ML) and deep learning (DL)) techniques for the detection of PMDs using lung sound signals [6, 9]. The benefits of DL methods are automated feature extraction, end-to-end learning, hierarchical feature representation, and improved accuracy, as those of the traditional ML-based techniques [10]. The Internet of Things (IoT) framework helps continuously monitor the patient's lung sound signal and transmits the signal into the cloud, where the ML or DL model analyzes it and provides the diagnostic outcome to detect PMDs and update healthcare providers [11]. Therefore, integrating DL and IoT improves the accessibility and efficiency for better healthcare management in detecting PMDs using lung sound recordings. The development and implementation of a novel DL algorithm and its deployment on the cloud-based framework are essential for automated and IoT-enabled detection of PMDs using lung sound recordings.

In literature, various ML and DL methods have been utilized to detect different PMDs using lung sound recordings [6, 9]. Bokov et al. [12] have utilized the short-time Fourier transform (STFT) of lung sound signals to evaluate features and used the support vector machine (SVM) classifier for the recognition of abnormal sounds (wheezes). Similarly, Kandaswamy et al. [13] have extracted the statistical features from the wavelet coefficients of lung sound signals and used multilayer perception (MLP) to classify normal and abnormal sounds. In another study, Shi et al. [14] applied linear discriminant analysis (LDA) in the wavelet domain of lung sound signal to reduce the dimension of the feature vector and used an artificial neural network (ANN) model to classify different abnormal sounds. A method based on the wavelet packet transform-based extraction of features from lung sound signals and ANN classifier has been used to classify normal and abnormal sounds [15]. Similarly, the method based on the use of linear prediction cepstral coefficients (LPCC) features of lung sound signals and the SVM classifier has been used for abnormal sounds (stridor) [16]. Sengupta et al. [17] have utilized the mel-frequency cepstral coefficients (MFCC) features and ANN model to classify normal and abnormal lung sounds. Similarly, in another study, the MFCC features of lung sound signals and the random forest classifier have been utilized to recognize pneumonia and asthma-based PMDs [14]. The empirical wavelet transform (EWT) domain features of lung sound signals and gradient boosting classifier have been used to detect asthma, COPD, and pneumonia using lung sound signal [1]. The time-domain, cepstral-domain, texture-based, and frequency-domain features of lung sound signals and different machine learning-based classifiers have been used to detect COPD and pneumonia classes [18]. The above-mentioned ML-based method's classification performance depends on selecting features and classifier parameters for automated recognition of abnormal lung sounds. In recent years, various DL methods have been utilized to detect different PMDs using lung sound signals [6]. Shi et al. [14] have utilized transfer learning and recurrent neural network models on the time-frequency domain (TFD) of lung sound signals to detect asthma and pneumonia classes. Fraiwan et al. [19] have used the convolutional neural network (CNN) and bidirectional long short-term memory (BLSTM) network for automated recognition of different PMDs using lung sound signals. In another study, Huang et al. [6] have compared the classification performance of ANN, CNN, and recurrent neural network (RNN) models using TFD representations of lung sound signals to detect PMDs. Baghel et al. [20] have introduced a new deep CNN model architecture to classify normal and abnormal (Wheezing, Rhonchi, and Crepitation) classes using TFD representations of lung sound recordings.

The existing methods are based on classifying abnormal and normal lung sound signals. A few methods in the literature have considered normal vs. asthma vs. COPD vs. pneumonia PMD classification schemes using lung sound signals [1, 20]. These methods have obtained less classification performance for detecting multiclass-based PMDs using lung sound recordings. The existing methods have not been deployed on the cloud-based framework for real-time detection of PMDs using lung sound signals. The ensemble DL model combines the predictions of multiple DL models, and it has advantages such as high accuracy, bias-variance trade-off, and resilience to overfitting [21]. The ensemble DL model has not been explored in joint TFD of lung sound signals for the automated detection of PMDs. The novelty of this chapter is to develop a TFD-based ensemble deep neural network (EDNN) for detecting asthma, pneumonia, and COPD using lung sound data. The important contributions of this chapter are written as follows:

- An EDNN based on the prediction of TFD-based deep representation learning (DRL) models is proposed to detect PMDs using lung sound signals.
- The DRL model is formulated using transfer learning-based pre-trained or frozen networks along with dense layers.
- The TFD-based EDNN model has been deployed on the cloud-based framework for IoT-enabled detection of PMDs.

The remaining sections of this chapter are organized as follows. The details regarding the lung sound signal database are written in Sect. 10.2. The proposed TFD-based EDNN model to detect PMDs using lung sound signals is explained in Sect. 10.3. The results, discussion of the work, and challenges in the design of IoT-enabled wearable sensor-based lung sound data monitoring systems are presented in Sect. 10.4. The conclusions of this chapter are drawn in Sect. 10.5.

10.2 Database for Lung Sound Signals

In this study, we have considered a publicly available lung sound database [22] to evaluate the proposed TFD-based EDNN approach to detect PMDs. This database contains 336 lung sound audio recordings from 112 subjects [22]. The average age of the subjects to record the lung sound audio data in the database is 50.5 years. The sampling frequency of each lung sound audio data is 4 kHz. The average duration of the lung sound recordings is 15 sec. In this work, we have considered 105, 15, 27, and 96 lung sound audio data from healthy (normal), COPD, asthma, and pneumonia classes to evaluate the PMD detection performance using the proposed TFD-based EDNN approach.

10.3 Proposed Method

The flowchart of the proposed method to detect PMDs using lung sound recordings is shown in Fig. 10.1. It mainly consists of three important stages: frame-based segmentation of lung sound recordings, TFD analysis of lung sound frames, and ensemble deep learning for the detection of PMDs. We have written a detailed description of each stage of the flowchart in the following subsections.

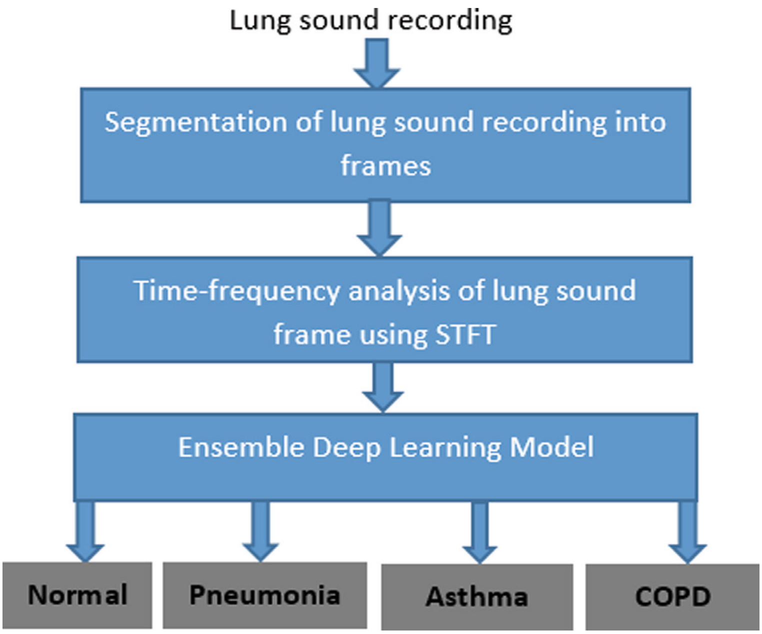

Fig. 10.1 Flowchart of the proposed Ensemble deep learning model on TFD for detecting PMDs using lung sound signals

10.3.1 Lung sound Data Augmentation and Segmentation

This work uses a 5-sec-based non-overlapping window to segment each lung sound recording into frames [1]. The number of lung sound recordings for COPD and asthma classes is less than those of normal and pneumonia classes. We have used data augmentation to generate lung sound recordings for COPD and asthma classes by adding the original lung sound signal for these two classes with additive white Gaussian noise (AWGN) noise of SNR values of 15 dB, 20 dB, and 25 dB.

10.3.2 Time-Frequency Analysis of Lung Sound

In this work, we have utilized the short-time Fourier transform (STFT), which is based on the windowed Fourier transform, to evaluate the TFD representation of each lung sound frame. For the lung sound frame, $z(m)$, of length N samples, the STFT is evaluated using the following mathematical expression, which is given as follows [23]:

$$Z(n,k) = \sum_{m=0}^{N-1} z(m)W(m-n)e^{\frac{-2j\pi mk}{N}} \tag{10.1}$$

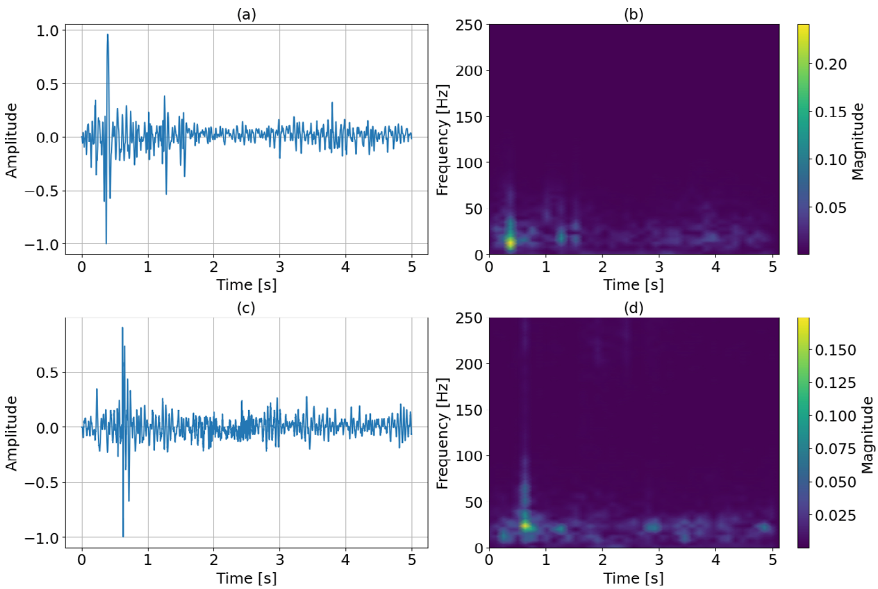

Fig. 10.2 **a** Lung sound signal plot for normal class. **b** Spectrogram plot of lung sound signal for normal class. **c** Lung sound signal plot for pneumonia class. **d** Spectrogram plot of lung sound signal for pneumonia class

where $W(m)$ is the window function and k is the frequency index with $k = 0, 1, 2, ..., N - 1$. The Hanning window with a window size of 1024 samples is used in this work to evaluate the STFT of the lung sound frame [23]. The lung sound signals for normal and pneumonia classes are displayed in Fig. 10.2a and c, respectively. Similarly, the spectrogram plots evaluated using STFT of lung sound signals for normal and pneumonia classes are depicted in Fig. 10.2b and d, respectively. It is noted that the characteristics and intensity distributions of lung sound signals are different in the joint time-frequency plane for normal and pneumonia classes. Therefore, we can use the joint TFD representation or image of the lung sound signal for automated detection of different PMDs.

10.3.3 Ensemble Deep Learning

In this study, we have developed an EDNN model for the automated detection of three PMDs (pneumonia, COPD, and asthma) and normal classes using TFD images of lung sound frames. The EDNN is formulated using the majority voting-based ensemble strategy [21] based on the decisions of binary classifiers. We have formulated six binary classifiers for the four class-based PMD classification tasks (normal vs. pneumonia vs. COPD vs. asthma). These binary classifiers are based on normal

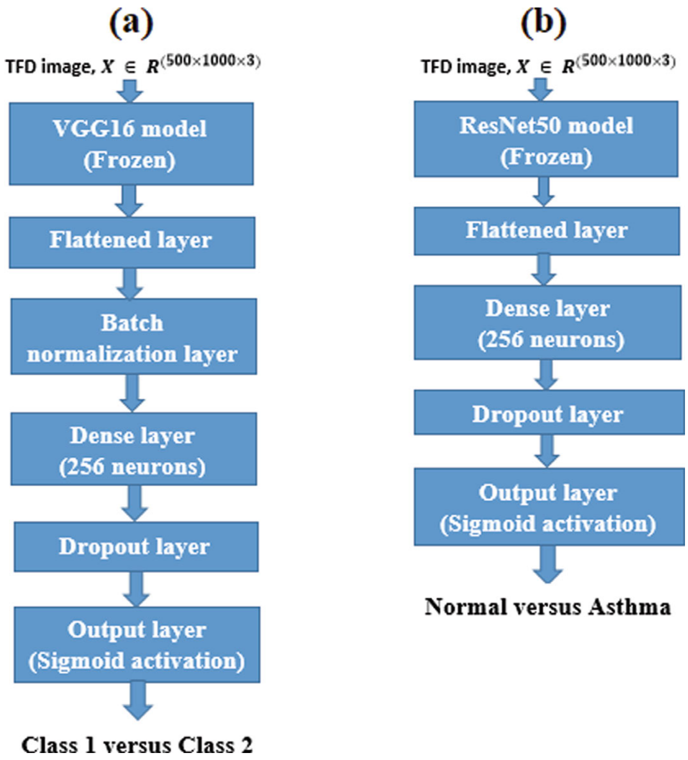

Fig. 10.3 **a** The deep learning model architecture for the classification tasks such as normal (N) vs. pneumonia (P), normal vs. COPD (C), asthma (A) vs. pneumonia (P), asthma vs. COPD, and pneumonia vs. COPD using TFD representation of lung sound signals. **b** The deep learning model architecture for the normal vs. asthma classification task

vs. asthma, normal versus COPD, normal versus pneumonia, asthma versus COPD, asthma versus pneumonia, and COPD versus pneumonia strategies. We have considered the ResNet50-based deep representation learning (DRL) model for the normal versus asthma classification task, as shown in Fig. 10.3b. The ResNet50-based pre-trained block [24] is used to extract features from the TFD image of the lung sound frame, and then the dense layer with 256 neurons, the drop-out layer, followed by the output layer (sigmoid activation), is used for classification. The drop-out factor of 0.1 is considered for the DRL model to classify normal versus asthma using TFD images of lung sound signals. The dropout layer is helpful in overcoming the overfitting issue of the DRL model [25]. Similarly, we have considered the VGG16-based DRL framework for the other five binary PMD classification tasks. The architecture of the VGG16-based DRL model is depicted in Fig. 10.3a. It uses the pre-trained or frozen VGG16 block [26] as a feature extractor, flattened layer, batch normalization layer, dense layer (256 neurons), drop-out layer, and output (sigmoid) layer, respectively. The dropout factor considered for the VGG16-based DRL model is 0.5. The training parameters, such as cost function as binary cross-entropy, optimizer as Adam with initial learning rate as 0.001, batch size as 32, and number of epochs as 30, are considered for all binary DRL models. These hyperparameters are chosen based on the grid search with criteria as the maximum value of the validation accuracy for the automated recognition of PMDs [10, 27]. After obtaining the class probability values for all six binary classifiers, we used soft-voting and hard-voting strategies [28] to formulate the EDNN model for the automated detection of pulmonary diseases. In the hard voting case, the majority voting or mode of the predictions of all six binary classifiers is used to obtain the final decision or output for detecting PMDs. Similarly, for the soft voting case, we have used weighted probability values of all six binary classifiers to obtain the final prediction of the EDNN model. The classification performance of the proposed EDNN model is evaluated using accuracy, F1-score, precision, and recall values [10]. These measures are computed from the confusion matrix of the 4-class-based PMD detection task.

10.4 Results and Discussion

The classification results of the EDNN classifier evaluated using the TFD images of lung sound recordings are depicted in Table 10.1. It is observed that apart from the normal versus COPD case, the deep representation learning-based binary classifiers have obtained accuracy, precision, F1-score, and recall values of 85.97%, 94%, 85.75%, and 78.33%, respectively, for the automated classification of lung sound signals. Similarly, in other binary classification tasks such as normal versus asthma, normal versus pneumonia, asthma versus COPD, asthma versus pneumonia,

Table 10.1 Classification performance of binary and EDNN models for detecting PMDs using lung sound signals

Classification task-based models	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
N versus A	90.09	84.85	98.25	91.06
N versus P	94.87	90.00	100	94.74
N versus C	85.97	94.00	78.33	85.75
A versus C	92.31	86.36	100	92.68
A versus P	96.67	93.44	100	96.61
P versus C	95.93	92.30	100	96.00
N versus A versus P (hard voting)	89.08	90.17	89.00	89.19
N versus A versus P (soft voting)	90.23	91.21	90.07	90.33
N versus A versus P versus C (hard voting)	85.04	88.75	84.84	86.56
N versus A versus P versus C (soft voting)	87.61	88.48	87.64	87.76

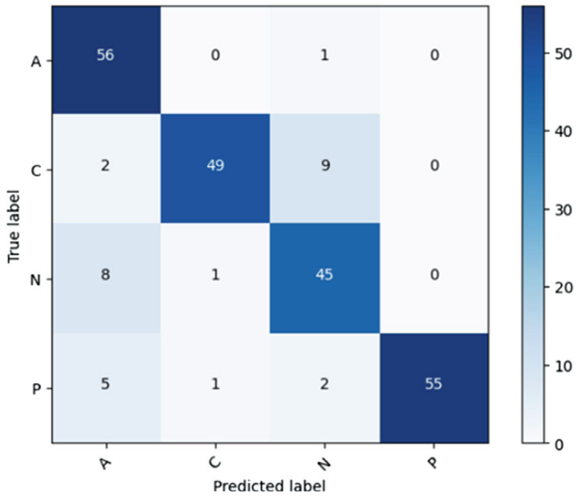

Fig. 10.4 Confusion matrix for N versus P versus A versus C-based PMD classification task evaluated using EDNN model

and pneumonia versus COPD, the DRL models have demonstrated accuracy and F1-score values of more than 90%. We have shown the classification results of the EDNN classifier for three-class and four-class classification tasks. For the normal versus asthma versus pneumonia-based classification task, the EDNN classifier with soft voting strategy obtained an accuracy value of 90.23%, which is higher than the EDNN with hard voting case using TFD images of lung sound signals. Similarly, for the normal versus asthma versus pneumonia versus COPD-based four-class PMD classification task, the EDNN classifier with soft voting case has produced an average accuracy value of 87.61% as compared to the EDNN model with a hard voting strategy. The confusion matrix evaluated for four-class-based detection of pulmonary diseases using TFD images of lung sound signals using EDNN with a soft voting strategy is depicted in Fig. 10.4. It is observed that the number of true positives for the asthma, COPD, normal, and pneumonia classes is 56, 49, 45, and 55, respectively. We have shown the t-SNE plot of the features extracted at the last dense layer (layer before the output layer) of the proposed EDNN model to detect PMDs. There is an overlap in the feature values of some lung sound signals for normal and asthma classes. During mild asthma episodes, the characteristics of the lungs sound pretty similar to those of the normal or healthy case [2]. Due to this reason, there is an overlap in the feature vectors for normal and asthma classes in the t-SNE plot (Fig. 10.5).

Furthermore, we have deployed the proposed TFD-based EDNN model on a WAPP for IoT-enabled real-time detection of PMDs using lung sound recordings. The WAPP of the proposed approach to detect PMDs is depicted in Fig. 10.6. The WAPP takes the input as the lung sound data, and it displays the TFD image corresponding to the lung sound data along with the prediction of the type of PMD using the EDNN classifier. The classification performance of the proposed TFD-based EDNN approach is compared with the existing DL and feature-based ML methods

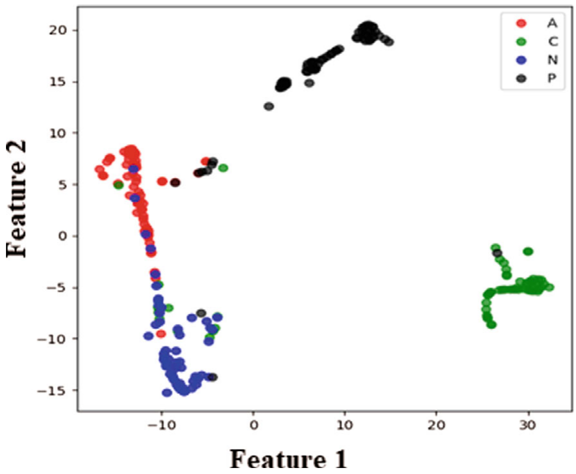

Fig. 10.5 t-SNE plot for the features obtained in the last layer (before output layer) of EDNN model using TFD images of test lung sound signals for normal (N), pneumonia (P), COPD (C), and asthma (A) classes

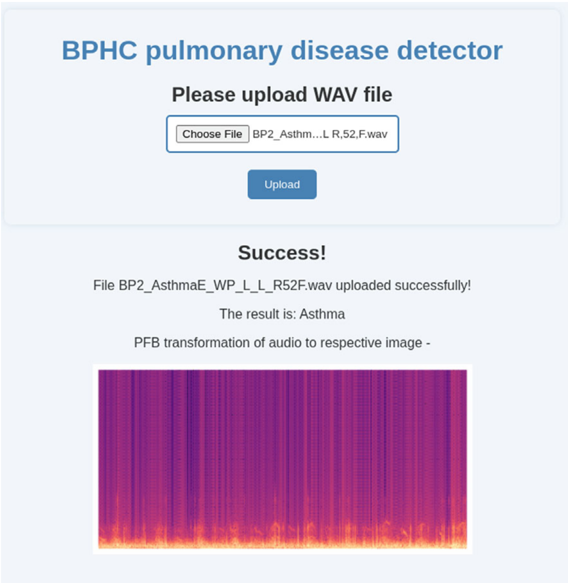

Fig. 10.6 Deployment of the proposed TFD-based EDNN model on the web application (WAAP) for the real-time detection of PMDs using lung sound audio data

for H versus P versus A-based PMD classification task, shown in Table 10.2. The MFCC features coupled with the random forest (RF) classifier have demonstrated an accuracy value of 72.93%, higher than MFCC features with the k-nearest neighbor (KNN) classifier to detect pneumonia and asthma-based PMDs using lung sound signals [14]. The deep CNN-based models and VGG-based transfer learning have produced overall accuracy values of less than 88% for normal versus pneumonia versus asthma-based PMD classification tasks using lung sound data [14]. The gradient boosting classifier LGBM) coupled with EWT-based features of lung sound signal

Table 10.2 Comparison with existing methods for normal versus pneumonia versus asthma-based PMD classification task

Methods used	Accuracy (%)
MFCC features extracted from lung sound signal, and k-nearest neighbor (KNN) classifier [14]	71.85
MFCC features extracted from lung sound signal and random forest (RF) classifier [14]	72.93
Two convolutions layer-based deep CNN model [14]	71.21
Five convolutions layer-based deep CNN model [14]	73.72
VGG-based transfer learner followed by Bidirectional gated recurrence unit (GRU) model [14]	87.41
EWT domain features of lung sound signal and light gradient boosting machine (LGBM) classifier [1]	84.76
TFD-based EDNN model (Proposed work)	90.23

have obtained the overall accuracy value of 84.76% [1]. The proposed TFD-based EDNN model has produced higher accuracy than the existing ML and DL-based methods for automatically detecting pneumonia and asthma-based PMDs using lung sound signals from the same database. In this study, only lung sound data have been utilized to identify PMDs automatically. In clinical studies, pulmonary hypertension is diagnosed based on cardiac and pulmonary data analysis based on chest X-rays, echocardiography, and CT scans [29]. The simultaneous recording and monitoring of heart and lung sound data will be very effective for diagnosing pulmonary hypertension and other PMDs [30]. Hence, the EDNN model can be explored using the joint TFD representations of heart sound and lung sound data to detect various PMDs.

10.4.1 Wearable Sensor-Based Lung Sound Analysis Applications

The wearable sensor-based recording of lung sound data coupled with the DL method is vital for the respiration monitoring and automated detection of PMDs. Wearable devices, like chest-mounted sensors (microphones embedded system) and smart patches, capture lung sound data from the subject non-invasively [31]. Wearable sensor-based lung sound data is contaminated with artifacts. Hence, developing different signal processing algorithms to eliminate these artifacts is challenging in obtaining cleaned lung sound data to diagnose PMDs accurately. The TFD analysis provides the variation of lung sound data concerning both time and frequency and offers vital information for machine learning or deep learning methods for the automated detection of PMDs. The proposed TFDEDNN approach does not require evaluating features in the time domain or frequency domain of lung sound data for automated detection of PMDs. The EDNN model directly takes the TFD images of lung sound signals to detect pneumonia, COPD, and asthma. Integrating IoT with a wearable sensor-based lung sound data recording system is interesting for real-time monitoring and automated diagnosis of PMDs. Several advantages of IoT-enabled wearable sensor-based lung sound data monitoring are telehealthcare monitoring, cloud-based web applications for real-time prediction of PMDs, and early warning systems for chronic or high-risk subjects [32]. Several challenges, such as the privacy and security of lung sound data when transmitted to the cloud, efficient power management and battery life for wearable-sensor-based lung sound data recording devices, and interoperability of machine learning or deep learning models, are involved while designing IoT-enabled wearable sensor-based lung sound data monitoring systems. Edge computing for the automated detection of PMDs using lung sound data has several advantages, such as low latency (the automated diagnosis is performed nearer to the lung sound recording system), immediate feedback (the patient and healthcare provider can receive immediate diagnostic decisions, lung sound data privacy, and security (lung sound data has not sent to the cloud and it is processed locally), reduced bandwidth usage and lower energy consumption as compared to the WAPP or cloud-based diagnosis of PMDs using lung sound data [33]. The field programmable gate arrays (FPGAs)-based edge computing devices offer parallel processing, low-latency, low-power, and hardware-level security as compared to microcontroller and Android-based edge devices for biomedical embedded system applications [34]. Hence, the FPGA-based embedded DL can be explored using the TFD representations of lung sound data to detect PMDs automatically.

10.5 Conclusion

The EDNN approach has been proposed in this chapter to detect pulmonary diseases using the TFD representation of lung sound recordings. The segmentation and STFT-based TFD analysis techniques have been applied to each lung sound recording. The TFD image of each lung sound frame has been given as input to the EDNN classifier to detect PMDs. The proposed TFD-based EDNN approach has been successfully deployed on WAAP for the IoT-enabled detection of three types of PMDs (asthma, COPD, and pneumonia) with an accuracy of 87.61%. The proposed approach has shown superior performance compared to the existing techniques for normal versus asthma versus pneumonia-based classification tasks. In the future, new DL-based architectures can be developed using TFD representations of lung sound data and their real-time implementation using edge devices for the automated detection of PMDs.

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Chapter 11
Are We There Yet? The Clinical Impact of In-Hospital Continuous Wearable Monitoring

Carlos Areia and Haipeng Liu

11.1 Introduction

Timely detection and response to patient deterioration are vital for patient safety in hospital wards [1–4]. Traditional intermittent monitoring, often relying on manual measurements by nurses and other healthcare professionals, suffers from several limitations. For example, a low frequency of observations can result in missed instances of patient deterioration occurring between checks. This delay in identifying worsening conditions can lead to delayed interventions, potentially increasing the risk of adverse events, including unplanned intensive care unit (ICU) admissions and increased mortality [5–7]. Manual vital sign monitoring is often inconsistent due to variations in recording practices and missed or delayed observations [8, 9]. The time-consuming nature of manual data collection and documentation can further strain already busy clinical staff. Balancing the need for regular observations with patient comfort, particularly during the night, is another challenge faced by nurses [10]. These limitations have prompted the exploration of alternative monitoring methods, leading to the development and increasing use of wearable monitoring systems (WMS).

Continuous monitoring of vital signs allows for earlier detection of potentially life-threatening conditions, giving healthcare professionals more time to intervene

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and prevent adverse outcomes [1]. As such, WMS offers a promising solution for continuous and less intrusive monitoring of vital signs [4, 11, 12]. These systems can capture physiological data at higher frequencies and detect subtle changes that may be missed with intermittent manual measurements. This continuous stream of data brings the potential to enable earlier identification of deterioration trends, allowing for timely escalation of care and potentially preventing adverse events [3, 4]. Despite the possible advantages, evidence supporting the impact of WMS hospital integration on patient outcomes remains inconclusive. Early studies have primarily focused on device feasibility and reliability, with many conducted in healthy volunteers rather than actual patients [4]. These limitations and lack of clinical implementation research assessment make it difficult to extrapolate findings to real-world clinical settings where patient populations are diverse, and health conditions can be complex [4]. Other barriers affecting WMS adoption include device reliability, maintenance, and wearability, amongst others [13]. Patient comfort, device fit, and ease of use significantly impact user experience and adherence [14]. Balancing device accuracy with wearability considerations is essential for the successful integration of WMS into clinical workflows [10].

The emerging combination of artificial intelligence (AI) with wearable monitoring represents a transformative shift in patient care, promising to improve patient safety, optimise clinical workflows, and reduce hospital costs. Despite these advantages, AI-powered WMS are still emerging, with early research revealing inconsistencies between the capabilities marketed by wearable device providers and the actual functionality observed. Understanding AI-WMS through various lenses—including practical applications, technological limitations, ethical concerns, and future opportunities—is essential to evaluate whether these systems truly represent a recipe for success or a potential disaster in the future of patient care [15].

Finally, the cost-effectiveness of WMS in hospital settings also remains an emerging area of study. Although WMS shows significant potential to improve patient outcomes by facilitating continuous vital sign monitoring, the financial impact of these systems is still under evaluation. It is suggested in the literature that WMS, if proven clinically efficient, may reduce healthcare costs by potentially lowering ICU admissions and shortening hospital stays. However, achieving these benefits involves navigating substantial implementation investment, device maintenance, system integration, and other costs [14, 16].

This chapter will hopefully shed some light on the current status of wearable monitoring in hospital implementation, what the current challenges and limitations are (in a less technical, more practical sense) and evidence supporting its clinical and cost-effectiveness, as well as discuss the emergence of AI in this technology. We will also use the experience on the virtual High Dependency Unit project [4] to give real cases as well as practical and actionable tips for research, development, testing, and implementation of wearable monitoring systems in the hospital environment.

11.2 A Rapid Summary of the Current Evidence on the Clinical Impact of In-Hospital WMS

In this section, we will overview the current evidence on the clinical impact of WMS in the hospital environment. For this, we are mainly focusing on systematic reviews that include studies comparing WMS with standard care (usually intermittent monitoring). Reviews conducted between 2018 and 2024 were used [1, 4, 14, 17, 18], including a multitude of studies and outcomes. In this section, we will mainly focus on early deterioration detection outcomes, such as unplanned ICU admissions, rapid or cardiac response team activation and clinical outcomes such as mortality, major clinical complications, length of stay and others.

One of the main proposed benefits of wearable WMS in hospital settings is their ability to detect early signs of deterioration, potentially reducing unplanned ICU admissions and rapid response team (RRT) activations. Traditional monitoring methods involve intermittent checks of vital signs, typically conducted every four to six hours in general wards. This can delay the detection of patient deterioration, as deterioration can go unnoticed between checks [4]. WMS aims to bridge this gap by continuously monitoring vital signs and alerting healthcare providers to physiological changes in real-time. In our meta-analysis of WMS in hospital settings, we included studies with varying results regarding ICU and RRT outcomes [4] and found no statistically significant reduction in ICU transfers or RRT activations for patients using WMS compared to those receiving standard care. We concluded that these mixed results could be due to variations in study designs, patient populations, and types of wearable devices used, highlighting the need for more controlled studies to establish definitive outcomes. Sun et al. (2020) also conducted a systematic review on the clinical impact of continuous monitoring in general wards, finding slight but inconsistent reductions in ICU admissions. Their review notes that while some studies reported reduced ICU transfer rates, these findings were not consistent across all studies, and larger trials would be necessary to substantiate any association between WMS and reductions in ICU or RRT activations [18].

Mortality and major complication rates are other critical outcome when evaluating the effectiveness of WMS. We evaluated the impact of WMS on these outcomes in a meta-analysis and found no significant reduction in mortality rates or major complication incidence among patients monitored with WMS compared to standard intermittent monitoring. We concluded that while continuous monitoring offers theoretical advantages for early detection, this has not been translated into measurable reductions in mortality or major complications in current studies. This was also due in part to the lack of robust large-scale trials, as well as the variability in device performance and response protocols in clinical settings [4]. In another review, some studies also indicated a potential trend toward lower mortality rates in patients monitored continuously, but these findings were also not statistically significant. The authors agreed with our review in showing that while WMS has the potential to detect physiological deterioration sooner, larger, high-quality studies would be needed to clarify the association between WMS and mortality reductions in hospital patients [18]. Interestingly, Eddahchouri et al. (2022) observed a trend towards fewer severe adverse events with WMS, although mortality rates remained largely unaffected, suggesting that even if WMS potentially allows for earlier identification of clinical deterioration, the benefits may not always extend to survival outcomes. One possible explanation is that WMS alone cannot guarantee early intervention; timely responses from clinical staff are also crucial for reducing mortality. The study suggests that, while WMS might aid in managing early deterioration, it does not replace the need for adequate staffing and response protocols [19, 20]. Additionally, Leenen et al. (2024) found that WMS implementation did not significantly impact the rate of major complications. While their study on postoperative patients suggested potential reductions in minor complications, it did not show a notable effect on the incidence of serious events [21]. This mixed evidence highlights the current limitations in establishing WMS as a primary tool for reducing mortality and serious complications, indicating a need for further rigorous studies.

Hospital length of stay (LOS) and readmission rates are important indicators of healthcare efficiency and patient recovery. In theory, continuous monitoring should also potentially reduce LOS by enabling earlier intervention and management of complications, thus allowing patients to recover more quickly, optimising beds, and saving hospital costs. However, evidence on the effect of WMS on LOS is varied. Leenen et al. (2024) conducted a recent study on patients with abdominal surgery and found that continuous monitoring reduced the median LOS from 5.5 to 5 days. This finding suggests that WMS can provide particular benefits in high-risk postoperative populations, as continuous monitoring can facilitate quicker interventions that reduce recovery time [21]. Bignami et al. (2024) also suggested that in surgical patients, WMS reduced both ICU admissions and LOS, suggesting a potential reduction in healthcare costs due to shorter hospital stays and fewer ICU transfers. This scoping review emphasised that continuous monitoring could support the early identification of complications, thereby reducing the likelihood of prolonged recovery periods. However, the review also highlights that these benefits might be specific to certain patient populations or types of surgery, rather than being generalisable to all ward settings [14]. In our meta-analysis, we noted that despite earlier detection capabilities, there was no consistent evidence to support LOS reductions with WMS in patients in general ward [4]. Eddahchouri et al. (2023) also reported no significant effect on hospital readmission rates, indicating that while WMS can help manage deterioration during the hospital stay, it may not impact the patient's condition sufficiently to prevent post-discharge complications and re-admissions [20].

In summary, the current evidence on the effectiveness of WMS for early deterioration detection and clinical outcomes remains inconclusive. Studies show potential benefits for ICU admissions and RRT activations, with some positive trend toward reductions in unplanned ICU transfers and RRT calls. However, mortality and major complication rates remain largely unchanged in most studies, suggesting that WMS alone may not be sufficient to improve survival outcomes without adequate staffing and timely intervention protocols. While some studies report reductions in LOS, particularly in specific high-risk groups such as patients with colorectal surgery, these findings are not consistent in all populations. One of the points that most of the included reviews in this analysis agree on is that future research should focus on large-scale randomised controlled trials with standardised protocols to better assess the impact of WMS on these early detection and overall clinical outcomes.

11.3 Current Practical Challenges and Limitations of Wearable Devices and Systems

One of the first steps before considering clinical testing and implementation is the reliability and accuracy of the device, and all wearable devices to be considered integration as well as the system itself need to be thoroughly tested before use [22]. It would be interesting to explore other types of challenges and limitations that can hinder hospital implementation of WMS and/or acceptance of patients towards this new technology. These can include more practical challenges such as device wearability or user interface complexity. And will allow us to explore more practical limitations that can sometimes be simple and easy to fix, but if not done appropriately and/or promptly, could potentially be the pitfall of WMS adoption in clinical environments [23].

We will start with a simple challenge: battery limitation. Studies on wearable technology emphasise that frequent battery replacements or recharging can disrupt continuous monitoring and place additional burdens on clinical staff. The power supply challenge is particularly pronounced in hospitals with limited resources or in settings where patients are not closely monitored by staff, highlighting the need for devices with longer battery life and energy-efficient designs [24].

Real case: Before implementing the system in the COVID wards, we were between two pulse oximeters with similar accuracy and conducted some interviews with the clinical staff. Interestingly, their choice was very easy due to one very simple and important practical detail. We thought that the nurses would prefer the smaller and more wearable device, however this one had to be charged or replaced twice a day, whilst the chosen pulse oximeter (bulkier and less comfortable) used 2 AA batteries that only needed replacement every 48 h of continuous use. As the goal of the WMS implementation was to reduce clinical staff exposure to COVID-19, it was clearly the optimal pulse oximeter to be implemented and a very easy choice for clinical staff.

Excess false alarms remain a significant issue with WMS, leading to alarm fatigue among healthcare providers. Weenk et al. (2017) pointed out that high rates of non-actionable alerts can desensitise staff to alarms, potentially undermining the effectiveness of continuous monitoring [9]. Alarm fatigue is a significant challenge when using WMS, as continuous data streams from these devices can trigger frequent alerts, many of which may not require immediate attention. Continuous monitoring of multiple physiological parameters can result in numerous alarms, contributing to clinician desensitisation to alerts, a phenomenon known as alarm fatigue. This issue is well-documented in research by Downey et al. (2020), which found that alarm fatigue could lead to delayed responses to genuinely critical events, as clinical staff became overwhelmed by the volume of notifications [25]. We also reported that data overload from wearable devices is a concern, as clinicians may struggle to interpret vast amounts of data without advanced analytics or decision-support systems in place, complicating timely decision-making and that there is a significant effort in minimising false alerts and optimising action from healthcare professionals whenever there is an alarm [4].

Tip #1: If developing a WMS, spend a considerable time working with clinical staff (both nurses, doctors, and everyone directly affected) to calibrate and refine the alert triggers to an optimal state of action, as staff can easily get desensitised and then the WMS will just be another ignored alarm contributing to the overall noise of the ward. The goal here should be to optimise alert/action ratio.

Wearable devices often lack comprehensive clinical validation across diverse patient populations and conditions. Regulatory approval for WMS is complex and inconsistent across regions, and many devices marketed for clinical use have not undergone rigorous testing in real-world hospital settings. Research suggests that many wearable devices are released with limited evidence supporting their efficacy, creating hesitation among healthcare providers regarding their use in critical settings. Furthermore, inconsistent regulatory standards globally create additional challenges for healthcare systems operating in multiple regions, limiting the scalability of WMS [14].

Tip #2: Actively involve hospital management, clinical staff, patients and relatives throughout all stages of device and system selection, design, development, and testing. During the research period, plan for qualitative interviews, focus groups, and mixed-methods studies.

Still, the introduction of WMS requires extensive training for clinical staff, as well as adaptation of workflows to accommodate the new technology, continuous data streams, and monitoring methods, amongst other required practical day-to-day adjustments to integrate and use WMS in daily practice. Traditional intermittent monitoring practices differ significantly from WMS protocols, which require staff to monitor and respond to continuous real-time data. Weenk et al. (2020) found that lack of adequate training could lead to misinterpretation of WMS data, resulting in either over-response to benign fluctuations or under-response to critical events . Integrating WMS into existing workflows requires significant adjustment from staff, particularly in interpreting new data types and managing alarm frequencies. Without sufficient training and workflow integration, WMS may be underutilised or incorrectly used, diminishing their intended benefits or resulting in significantly less adoption of WMS [24]. Wearable devices introduce new logistical demands for healthcare facilities, including regular device cleaning, calibration, and inventory tracking. Bignami et al. (2024) highlighted that devices used in clinical settings require regular maintenance to ensure consistent accuracy and hygiene, especially in settings where they are used by multiple patients. In addition, staff must manage device power levels and connectivity, adding to their workload. In high-demand hospitals, such as those with high patient-to-staff ratios, this additional workload can strain healthcare resources, reduce staff efficiency and adopt this technology [14]. Whenever possible, research and technical teams should take the operational responsibility for the wearable devices and systems and take the extra load off already strained healthcare professionals.

Tip #3: This complements the other tip above. Less is more, the fewer actions and steps clinical staff and patients need to take to use devices/WMS, the more likely the system is to be successfully integrated and accepted by clinical staff. Spend time and resources designing the devices/system both for minimal disruption of staff activities and supporting them with operational/maintenance tasks whenever possible.

Real case: Prior to the onset of COVID-19, we had been evaluating our WMS along with various devices in surgical wards. We conducted interviews with clinical staff and focus groups [10], accuracy and validation studies (see the setup for our hypoxia study in Fig. 11.1 [8, 26, 27]), wearability testing (Fig. 11.2) [13]. Additionally, we were in the process of setting up a clinical trial in the surgical wards, so management and staff were aware of our work and project status that made the urgent COVID implementation easier [27]. Even though management and staff were aware of our project, considerable training and integration were still required although we have optimised the system to make sure disruption was minimised to clinical staff (for example, there were research members available for device swapping, calibration, setup, trouble-shooting, etc.…).

The wearability of monitoring devices significantly affects patient compliance. Many wearable devices, particularly those worn on the chest or finger, can be uncomfortable during prolonged use, leading to patient non-compliance and compromised data reliability. Areia et al. (2021) observed that wearable devices could cause skin irritation, discomfort, or restrictions in movement, leading patients to remove devices intermittently, thus interrupting continuous monitoring [4]. Downey et al. (2020) similarly found that the discomfort of certain wearable devices reduced their usage time and effectiveness, as patients in hospital settings are more likely to comply with monitoring if devices are minimally intrusive and comfortable. Device wearability is one of (if not the biggest) reasons for non-adoption, however, despite the number of devices in the market and being actively tested/used in patients, there are a very small number of published wearability studies [13]. In our view, this is one of the easiest, simplest, and most basic step that is often ignored and can have a massive impact on the adoption of this technology. It does not matter how accurate a device is if it is painful or uncomfortable to wear for prolonged periods, patients will remove it, and data will be lost.

Tip #4: If you are developing/selecting devices for your system. Everyone on your team should wear all devices continuously for a week before considering putting them on patients. Complete a wearability report and analyse the results.

Privacy and data security are significant challenges for WMS, given that these devices continuously collect and transmit sensitive patient data. The security of patient information is a high priority in healthcare settings, and wearable devices

Fig. 11.1 Hypoxia study day set-up. Legend: 1: Tablets linked with wearable devices (4 Samsung TAB A, each linked with one of these: AP-20, WristOX2 3150 BLE, CheckMe™ O_2 and VitalPatch®. 1 iPad four connected to the wavelet). 2: Resuscitation trolley and oxygen. 3: Oxygen in nitrogen cylinder. 4: hypoxicator apparatus. 5: Philips monitor (model MX450) connected to laptop (IX trend software). 6: drip stand with the arterial line pressure bag. Extracted from the original protocol [26] (CC BY 4.0)

must comply with regulations such as GDPR and HIPAA, which require stringent data protection measures. Implementing secure data protocols for wearable devices can be complex and costly, but is essential for building patient trust and ensuring regulatory compliance.

The initial costs associated with implementing WMS can be prohibitive, particularly for healthcare facilities with limited budgets. Hospitals must invest in wearable devices, network infrastructure, and staff training, which represent a substantial financial commitment. Additionally, ongoing costs include regular device maintenance, software updates, and battery replacements, all of which contribute to operational expenses. Leenen et al. (2020) highlight that WMS may not be economically viable in all settings, especially where financial resources are constrained [1]. Although WMS theoretically offers cost-saving potential by reducing ICU admissions and shortening hospital stays, there is limited concrete evidence of its cost-effectiveness (more on this below in the cost-effectiveness section of this chapter). Studies often emphasise potential clinical benefits, but lack comprehensive cost analyses, making it challenging for hospitals to assess the overall financial impact. Without robust data on direct and indirect cost savings, administrators may be hesitant to invest in WMS

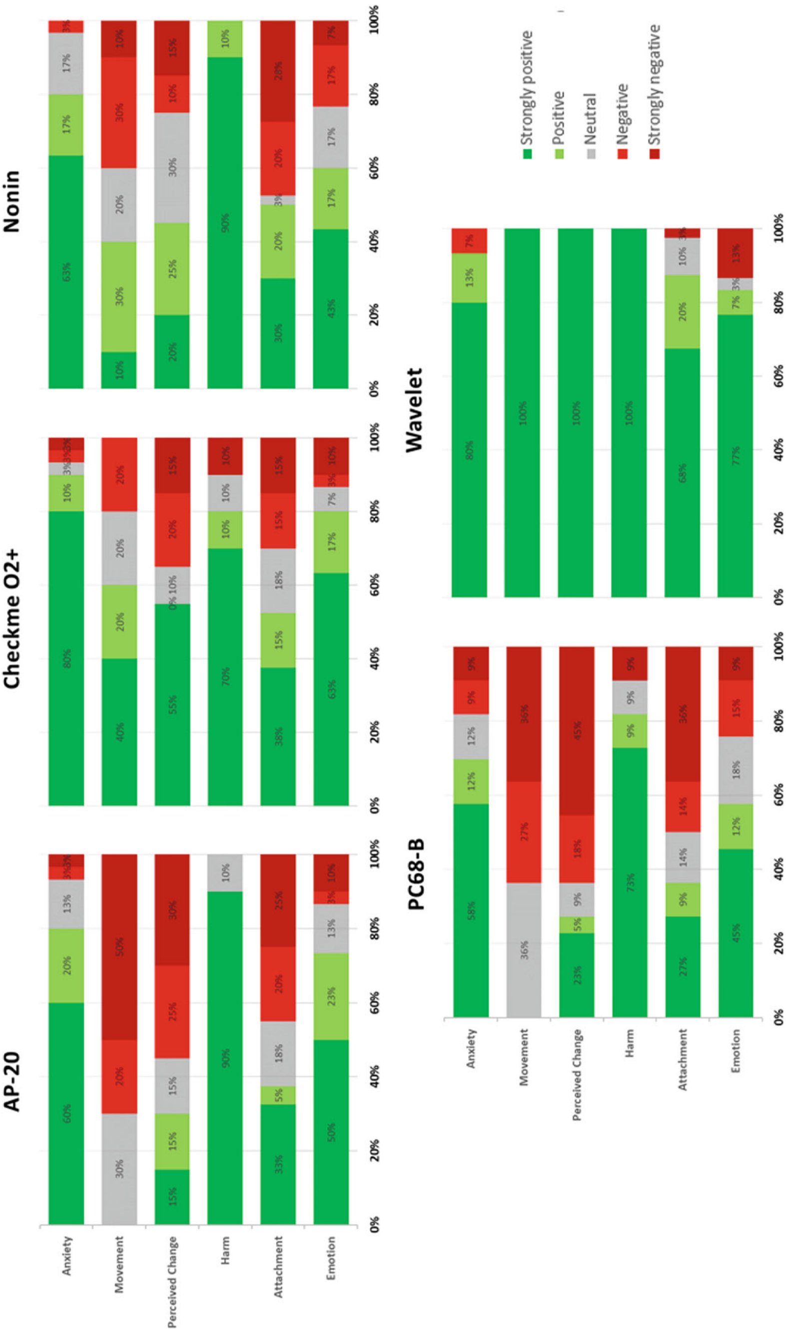

Fig. 11.2 Comfort Rating Scale scores for each chest patch device. Green represents the percentage of positive outcomes and red represents the percentage of negative outcomes. Extracted from Areia et al. 2020[13] (CC-BY 4.0)

on a large scale, especially given the high initial implementation and maintenance costs.

Although wearable monitoring systems offer numerous theoretical benefits in improving patient care through continuous monitoring, several practical challenges limit their broad adoption. Technical issues such as device accuracy, power management, and connectivity reliability must be resolved to ensure reliable monitoring. Clinical challenges such as alarm fatigue and data overload hinder the usability and effectiveness of WMS, while operational challenges related to training, maintenance, and workflow adaptation add further complexity. Financially, the high costs and uncertain cost–benefit ratio make WMS implementation difficult to justify without strong evidence of cost-effectiveness. Future advancements in device technology, regulatory standardisation, and comprehensive cost analyses will be essential to address these challenges and unlock the potential of wearable monitoring in clinical practice.

11.4 Artificial Intelligence and WMS: Recipe for Success or Disaster?

The combination of AI with wearable monitoring in healthcare represents a transformative shift in patient care, promising to improve patient safety, optimise clinical workflows, and reduce hospital costs amongst many other opportunities. Despite these advantages, AI-powered WMS are still emerging, with most studies revealing inconsistencies between the capabilities marketed by wearable device providers and the actual functionality observed [15]. For example, one of the WMS challenges previously discussed in this chapter is alarm fatigue, where an excess of non-critical alerts can desensitise staff, leading to ignored or delayed responses to critical events. AI-enhanced WMS can potentially address this problem by using algorithms to adjust alarm thresholds in real-time and personalise it to each patient's status and history, but their success has been inconsistent and scarcely reported in the literature. Although there is the potential for AI to significantly reduce noise and false alerts through adaptive thresholding and artefact removal, the sensitivity of these systems to genuine clinical deterioration remains a concern; certain settings may inadvertently filter out critical alerts if threshold adjustments are not fine-tuned. This limitation highlights the need for rigorous calibration and validation of alarm algorithms before these systems are even considered for deployment. Currently, there are very few truly AI-powered WMS, as most use fixed alert thresholds [15].

Another critical challenge to advance AI in WMS is the need for regulatory oversight and transparency in AI deployment. While some device providers advertise "advanced AI", few disclose the exact workings of their algorithms, making it difficult for healthcare providers and regulatory bodies to assess efficacy. Transparent reporting on the algorithms, including their training datasets, performance metrics, and adjustment protocols, is necessary to properly evaluate these systems. Regulatory bodies must also establish guidelines to ensure that AI algorithms are validated not only for technical performance but also for clinical safety and efficacy across diverse groups of patient [15].

Tip #5: If using AI on your devices/systems, be as transparent as possible throughout. This will help build stakeholder trust and acceptance during testing, implementation and use.

While AI in WMS presents significant promise for transforming hospital care, there remains a considerable amount of work to be done to address the challenges and limitations that currently impede its potential clinical impact. The gap between marketed capabilities and actual functionality underscores the need for advancements in adaptive algorithms, rigorous clinical validation, and transparency in AI implementation. However, it is clear that achieving the full potential of AI-enhanced WMS will require not only technological progress but also a comprehensive, patient-centred approach that integrates clinical staff feedback and real-world usability. Despite these challenges, AI's potential to personalise monitoring, contribute to the early detection of patient deterioration, and optimise clinical workflows should not be discarded. As mentioned previously, large-scale RCTs are essential to validate the clinical benefits of these systems. Until these trials are completed, the implementation and validation of AI in wearable monitoring will likely remain limited, constraining its potential to meet marketed promises in real world clinical practice. With continued research and investment, AI-powered WMS is well-positioned to deliver on its promise, evolving from simple monitoring solutions to sophisticated systems capable of revolutionising patient care. As we push forward, the focus must be on refining these technologies to ensure they not only enhance patient safety and healthcare efficiency, but also seamlessly integrate into the everyday realities of clinical practice, in a safe, pragmatic, and ethical manner.

11.5 Potential Cost-Effectiveness of Implementation of WMS Inside the Hospital

The cost-effectiveness of WMS in healthcare settings remains an emerging area of study. Whilst wearable systems hold significant promise for improving patient outcomes by enabling continuous monitoring of vital signs, the financial impact of these systems is rarely explored. Current evidence suggests that WMS if proven clinically efficient, can reduce healthcare costs by potentially lowering ICU admissions and shortening hospital stays. However, achieving these benefits involves navigating substantial implementation expenses, device maintenance, and system integration challenges [1]. Below is an analysis of the financial considerations, potential benefits, and limitations of WMS cost-effectiveness as suggested by the available (albeit limited) research.

Despite the lack of strong evidence, a cost-utility analysis by Javanbakht et al. (2020) found that continuous monitoring in high-risk surgical patients was potentially cost-effective in preventing adverse events that require critical interventions [28], and more recently, Holmes et al. (2024) model-based cost-utility analysis found that automated notification systems for deteriorating patients could reduce ICU admissions and emergency interventions, resulting in fewer ICU costs [16]. This could translate into financial savings, particularly in high-volume hospitals, where ICU resources are costly and beds are often limited. By facilitating timely interventions, WMS also has the potential to reduce the duration of hospital stays and prevent complications that can otherwise extend a patient's recovery period or the probability of readmission. This recent study suggested that continuous monitoring could lower LOS in general wards, leading to reduced overall hospital costs. This reduction in LOS was a significant contributor to the system's cost-effectiveness, particularly in cases where early warnings helped prevent more serious health events that would require prolonged stays [16]. Javanbakht et al. (2021) similarly found that continuous respiratory rate monitoring with wearable devices in pneumonia patients shortened LOS and reduced ICU stays and these reductions contributed to significant cost savings, making the system a dominant strategy over a lifetime horizon in pneumonia patients [28]. In Downey et al.'s (2020) feasibility study on continuous monitoring in postoperative patients, the findings also indicated that patients in the continuous monitoring group experienced fewer readmissions within 30 days [25]. The reduction in readmission rates resulted from quicker interventions and improved postoperative monitoring, which also helped to reduce the average cost of patient care per admission.

11.5.1 Quality-Adjusted Life Years (QALYs) and Long-Term Cost Utility

QALYs provide a measure of the quality and quantity of life gained through a medical intervention. Studies that measure QALYs in relation to WMS have found promising results. Holmes et al. (2024) used a QALY model to calculate the cost-utility of automated monitoring systems, reporting a positive incremental gain in QALY and associated lifetime cost savings for patients. This long-term benefit suggests that WMS could provide a valuable cost-effective solution by improving survival rates and quality of life, particularly in patients who experience frequent deterioration, such as those with chronic conditions. In pneumonia patients [16], Javanbakht et al. (2021) also showed a cost-effective gain in QALYs through continuous respiratory monitoring, noting that the intervention was both cost-saving and life-extending. This study found that WMS could be highly effective in managing respiratory conditions, where early detection of deterioration significantly reduces both mortality and long-term healthcare costs [28].

11.5.2 Upfront and Ongoing Costs of WMS

However, the initial and recurring costs of implementing WMS are substantial and present significant barriers. Initial costs include purchasing devices, integrating them into existing healthcare systems, training healthcare staff, and others. Recurring costs involve device maintenance, regular calibration, and ongoing technical support, as well as compliance with data privacy and security standards, etc. Adopting wearable technology requires significant initial investment, especially for hospitals that implement automated systems on general wards. Purchase costs can vary widely based on the number of devices and the specific monitoring functions they provide [16]. The cost of system integration, as WMS must work seamlessly with electronic medical records (EMR) and early warning systems to be fully effective. These cumulative expenses may offset some of the cost savings from reduced ICU transfers and shorter hospital stays, making it harder for hospitals with limited budgets to justify the investment. While WMS shows promise in high-risk or post-surgical patient populations, where early detection of complications can prevent costly escalations, its cost-effectiveness is even less clear in broader, lower-risk populations [14]. Other studies have noted that most of the research on WMS focuses on specific high-risk groups, limiting the generalizability of cost benefits across different patient demographics. Further studies are needed to assess whether the financial benefits of WMS can extend beyond high-risk groups [1, 21].

In summary, while WMS has the potential for cost savings through reduced ICU admissions and shorter hospital stays, especially in high-risk populations, current evidence on direct financial benefits remains limited. The significant initial costs, maintenance, and integration challenges of WMS add complexity to its cost-effectiveness, and without substantial cost analyses, healthcare providers lack the comprehensive data needed to support widespread adoption. Together with bigger and better RCTs, these should include detailed cost-effectiveness sub-studies in the next few years. Then, at a later stage, economic studies with a broader scope should be conducted to prove the overall cost efficiency of these systems, focusing not only on high-risk patients but also on lower-acuity populations, to determine whether WMS can be a cost-effective solution in diverse healthcare settings. Although its clinical and cost-effectiveness still needs to be proven with robust evidence, the outlook is promising, indicating that hospitals could potentially offset the cost of WMS devices over time, especially in high-risk populations.

Tip #6: Consider a cost-effectiveness evaluation of your device/system.

Tip #7: Plan for high-risk populations. Studies indicate that WMS is most cost-effective in high-risk patient populations, where early detection of complications yields the greatest financial gain.

11.6 Are We There Yet? Final Reflections and Suggestions for Next Steps

Although it seems that the future of healthcare using WMS, and possibly AI or other combined technologies is near; there are several methodological and practical challenges that need to be addressed for a thoughtful and safe implementation of this promising technology. First, we need bigger and better designed RCTs to properly test and compare WMS with standard care, especially when integrating AI (where, in reality, barely any applied research has been made). To date, although promising, past studies have been either small RCTs or bigger before-after studies but with multiple confounders impacting the results. We agree with Leenen in his recent review conclusion stating that *"Widespread implementation of wearable wireless sensors for continuous vital signs monitoring systems on the general ward and potentially outside the hospital seems inevitable."* However, more funding and collaboration are needed to reach a definitive conclusion on the clinical and cost-effectiveness of WMS [21]. At present, several teams conduct smaller studies developing, testing, implementing and evaluating these devices and systems throughout the world.

For developing/working with hospital WMS, here is a summary of the tips given in this chapter. Collaborate with other teams, wear all devices for at least a week before testing it on patients, remember that "less is more" (this is applicable for almost everything, such as number of devices, optimising actionable alerts, minimising disruption and actions from clinicians), include cost-analysis and qualitative methods in your research, plan to start with high-risk populations for greater impact, involve stakeholders (especially clinical staff and patients) and be transparent throughout all steps.

Despite significant progress over the past decade, unfortunately, we are not yet there when it comes to the implementation of WMS in hospitals. Although current evidence is encouraging, large RCTs are urgently needed to be able to prove WMS worth in deterioration detection, clinical outcomes, and cost efficiency. We use this opportunity to send a call to action to hospital WMS research groups and departments to consider collaborating with other teams to design and conduct large high-quality RCTs.

Search Strategy

app.dimensions.ai/discover/publication?search_mode = content&search_text = (wearabl* OR ambulat* OR wireless OR telem* OR biosens* OR contactl* OR cablel* OR sonsor* OR "non contact" OR noncontact*) AND ("vital sign" ~5 OR "blood pressure" ~5 OR temperature OR therm* OR "heart rate" ~ 5 OR "respiratory rate" ~5 OR "breathing rate" ~5 OR "pulse rate" ~ 5 OR respiration OR breathing OR systolic OR diastolic OR oxygen OR saturat* OR fever OR vitals OR "early warning" ~ 5 OR "risk assessment" ~5) AND (hospit* OR admitted OR surg* OR recover* OR care OR icu OR itu OR critical OR emergency OR patient) AND (deteri* OR worse* OR death OR seps* OR dead OR predict*) &search_type = kws&search_field = text_search&order = relevance.

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Abbreviations

AI	Artificial Intelligence
ICU	Intensive Care Unit
LOS	Length of Stay
QALY	Quality-Adjusted Life Year
RCT	Randomised Controlled Trial
RRT	Rapid Response Team
WMS	Wearable Monitoring System

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Chapter 12
An Overview of Emerging Wearable Sensors in the Management of Chronic Diseases

Fatima Ali, Kehkashan Kanwal, Kartikeya Walia, Syed Mehmood Ali, Haipeng Liu, and Syed Ghufran Khalid

Abstract Wearable sensors represent a transformative advancement in the healthcare industry, they provide continuous non-invasive monitoring of physiological parameters. This chapter is devoted to an overview of wearable sensors and their types, together with the underlying technologies enabling their functionality. The chapter emphasizes the application of wearable sensors in the management of chronic diseases, underscoring their roles. Furthermore, wearable sensors, by providing data in real-time, enable individualized treatment planning, improve patient adherence, and facilitate early detection of disease exacerbations. These are profound effects that can reduce healthcare costs, improve patient outcomes, and streamline clinical workflows. It discusses the up-to-date active trials and developments in this area, highlighting further innovations underway and future directions. This analysis places wearable sensors at the very heart of revolutionizing chronic disease management and modernizing the delivery of healthcare.

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12.1 Introduction

Wearable sensors can accomplish the current needs as an emerging technology with the potential ability to sense changes in a human's biological state. This technology can be fitted into everyday things such as glasses, watches, and clothes. Wearable sensors are crucial in the microelectronics industry as they monitor physiological movements and signals [23, 24]. There are several fabrication procedures used to design and develop these sensors and then integrate them by incorporating communication modules meant for transmitting or receiving signals. Handheld devices that support real-time monitoring of physiological factors have already had an enormous impact on several industries, from the healthcare sector to the fitness industry. Wearable sensors enable personal health monitoring, clinical diagnostics as in Fig. 12.1, and even occupational safety. This sensor incorporation has changed the way we can connect to physiological data. Advancements in technology and the ability of electronics to be so miniature have enabled compact, efficient, and highly functional devices. This facilitates continuous data collection, allowing insights into health trends and performance metrics. The sensors collect real-time data from the body and process the information to gain valuable insights into several health parameters. These range from simple activity-tracking devices to high-end systems that track several different physiological signals to the best of their abilities. Therefore, have significant roles in the healthcare sector, in remote patient monitoring, providing doctors with critical data in time and making effective patient care possible beyond the traditional clinical setting [47].

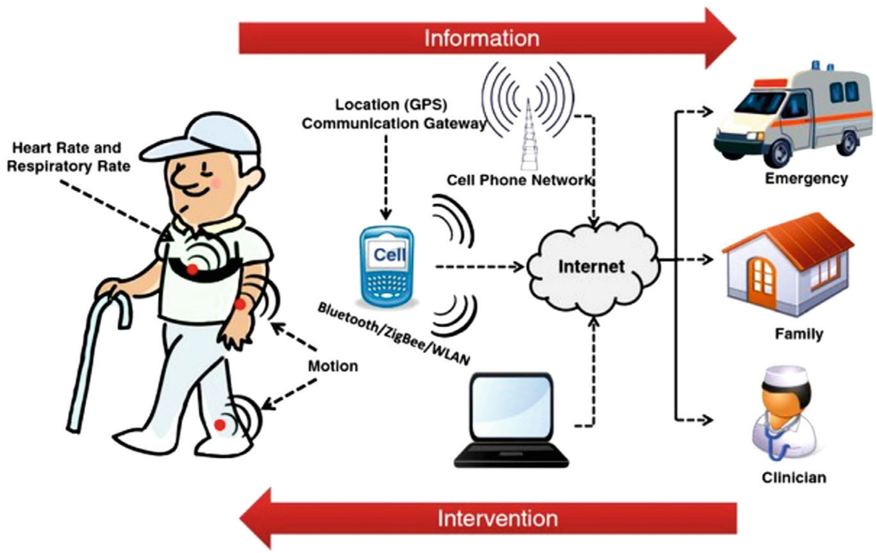

Fig. 12.1 Remote health monitoring system based on wearable sensors and wireless communication, reprinted from Smith et al. [47] under CC-BY 4.0 copyright license

Wearables in sports and fitness allow devices to track vital signs, activity levels, and performance metrics in a way that allows people to optimize their training routines and improve general health [51]. The idea of wearable sensors is decades old, dating back to the early examples of simplistic heart rate monitors, such as Holter monitors used for continuous heart monitoring and pedometers [7]. The progress, however, has been considerable since the days when more sophisticated sensors, advanced materials, microelectronics, wireless communication, and data processing started making their contributions, catalysing the advancement of wearable devices. In this evolution, flexible electronics and the integration of microelectromechanical systems have played a very critical role as they have made the devices more versatile, user-friendly, and varieties of designs possible [26]. These developments have fostered the invention of sensors that are increasingly being made not only to achieve higher accuracy but also in reduced sizes, more comfortable, and capable of continuous monitoring.

12.2 Types of Wearable Sensors

Wearable sensors play an increasingly important role in health monitoring and personal welfare technology [36]. They are embedded in devices that can continuously track real-time physiological parameters. The most commonly used types of sensors are accelerometers, gyroscopes, heart rate monitors, electrocardiogram (ECG) sensors, electromyography (EMG) sensors, temperature sensors, and bioimpedance sensors. These wearable sensors have changed the face of chronic disease management by allowing continuous monitoring with real-time data to back up actions for better treatment. Therefore, each category of wearable sensors serves specific functions, measuring a specific physiological parameter.

Most prominent among the wearables are heart rate and rhythm sensors, typically based on electrocardiogram technology. These sensors generally come embedded in either a smartwatch or a chest strap and are central in the management of various diseases, such as arrhythmias, heart failure, and hypertension. They will enable the constant monitoring of heart rate, thus alerting the healthcare providers to irregularities in the patient, avoiding severe cardiac events [21].

Another major category includes glucose monitoring sensors, which are very vital in the management of diabetes. The continuous glucose monitoring systems measure interstitial glucose by using minimally invasive devices that involve inserting a small sensor under the skin. These sensors allow for real-time updates of glucose levels, allowing for timely interventions against hyperglycaemia or hypoglycaemia. The development of the CGM has improved the quality of life of patients with diabetes by reducing the number of finger-prick tests and providing better glucose control [30]. Respiratory sensors are either part of smart patches or chest bands and measure respiratory rate and lung function. These help in the management of chronic respiratory diseases, such as asthma and chronic obstructive pulmonary disease (COPD). They maintain a continuous check on breathing patterns and raise an alert in case of exacerbations,thus, it allows early intervention and reduction in hospital admissions [19].

A critical tool in managing a chronic disease is the wearable blood pressure monitor. These devices, are often integrated into wristbands or upper-arm cuffs and are worn to monitor blood pressure continuously, offering invaluable insights into hypertension management. With the continuous monitoring of blood pressure, it would be easier to adjust medication and make lifestyle modifications to prevent complications such as stroke and heart disease [8].

In addition to this, activity trackers that include accelerometers and gyroscopes are the most common devices for measuring physical activity, sleep, and sedentary behaviour. Such sensors could be of help in all chronic conditions, especially those associated with obesity, cardiovascular diseases, and arthritis, by providing feedback on one's physical activity, which may be useful in managing weight, mobility, and general physical health. The temperature sensors, normally in wearable patches, measure skin temperature. Skin temperature could be key in detecting an important symptom: fever in many chronic conditions, such as infectious complications in diabetes or respiratory diseases. Its detection could trigger early medical evaluation and treatment [9].

Finally, wearable sensors that monitor oxygen saturation, like pulse oximeters, are of the essence to patients with chronic respiratory and cardiac conditions in the final. The blood oxygen level is continuously monitored by the device, which is particularly important in diseases like COPD and heart failure, where the level of oxygen may fluctuate greatly [14].

Integration of different wearable sensors as in Fig. 12.2, into the management of chronic diseases creates the potential benefits of increasing patient engagement, monitoring, and early medical interventions. Healthcare providers can, therefore, use such data to gain insights about more personalized treatment strategies and offer better care services to their patients.

12.3 Technologies and Key Features in Wearable Sensors

Wearable sensing devices have hugely evolved in today's modern landscape, where multiple technology-related areas have seen new advancements. Such sensors are deeply integrated into devices worn on the body for applications such as healthcare, fitness, and daily consumer electronics. Technologies and characteristics backing these devices focus on the miniaturization of components, wireless communication, low-power systems, and sophisticated data analytics.

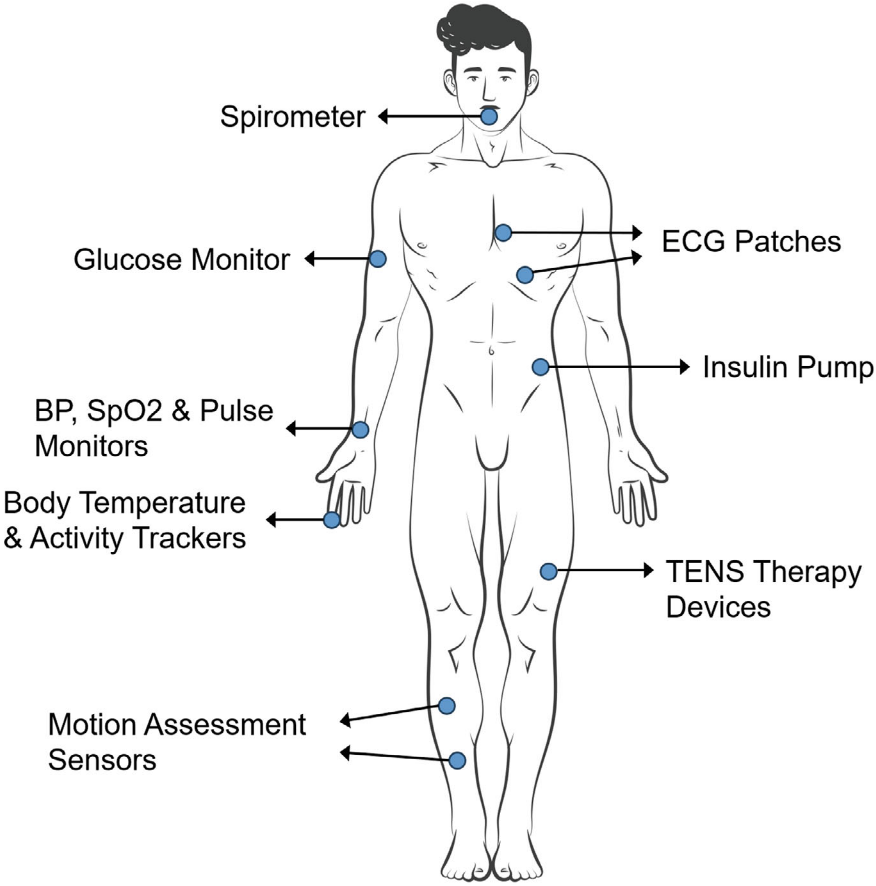

Fig. 12.2 Types of wearable devices for health tracking and patient care, the body shape outline icon from freepik.com under free license

12.3.1 Miniaturization and Integration

One of the most important facets in the development of wearable sensors has been the miniaturization of electronic components. MEMS advances allowed for the production of small, highly sensitive sensors that easily embed within wearable devices. Such components include accelerometers, gyroscopes, magnetometers, and others that provide precision in monitoring physical activity and movement. It allows continual monitoring of heart rate, body temperature, and glucose levels, among other parameters that give a holistic view of one's health status, by integrating multiple sensors into a single device [18].

12.3.2 Wireless Communication

In functionality, wireless communication technologies are at the centre of wearable sensors. They allow data transfer between sensors and other devices, such as smartphones and computers, and ensure all this is done seamlessly. BLE has emerged as a standard for short-range communication in wearables because of low power consumption and a strong connection. The BLE, with real-time monitoring and data synchronization, allows applications such as fitness tracking and remote patient monitoring. Other technologies, including Near Field Communication and Wi-Fi, also foster the connectivity and usability of wearable sensors with other medical devices for domestic monitoring [39].

12.3.3 Energy Efficiency

Energy efficiency has been one of the most significant features in wearable sensors since most of the devices normally use compact batteries with minimal capacity. The creation of low electronic power and efficient power management systems has enabled a lengthy life for such wearable devices. Techniques like duty cycling—the sensor cyclically goes through active and sleeping modes—result in drastically low power consumption compared to constant operation. Moreover, energy harvesting technologies that scavenge energy from the movement of the user's body or environmental sources are being considered as an adjunct for supplementary power supply to traditional batteries, promising self-sustainability in wearable devices [22].

12.3.4 Advanced Data Analytics

Wearable sensors can generate large volumes of data that are relatively complex to be analyzed without advanced analytics methods. Machine learning and AI techniques are increasingly being used in the analysis of sensor data to permit more accurate, personalized health and activity monitoring, as exemplified in the prediction of cardiovascular risks [12]. These techniques can identify patterns and anomalies in the data, facilitating early detection of health issues and providing personalized recommendations for users. Moreover, the cloud computing platforms scale up solutions that help store huge quantities of sensor data and process them to support sophisticated health monitoring systems [20].

12.4 Applications in Chronic Disease Management

Wearable sensors can be minimized and embedded into different medical devices [55]. The can measure different types of physiological parameters including biomechanical, electrophysiological, and biochemical signals and biomarkers (Fig. 12.3a). These biomarkers reflect the functioning of different organ systems, therefore can be used in the screening, diagnosis, prognosis, and management of various chronic diseases (Fig. 12.3b).

12.4.1 Diabetes

Wearable sensors are the future of diabetes management, providing continuous and real-time monitoring of key physiologic parameters. Continuous glucose monitors and insulin pumps give finer details in the management of diabetes giving minute

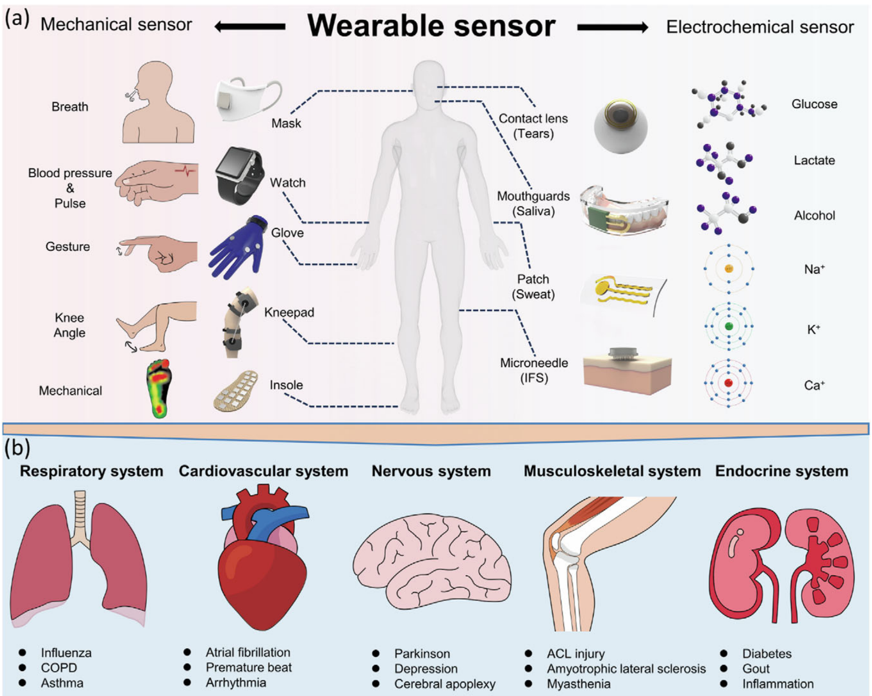

Fig. 12.3 Application of wearable sensors for chronic disease monitoring. **a** Different types of sensors and physiological signals. **b** Applications in different organ systems and diseases, reprinted from Xue et al. [55] under CC-BY 4.0 copyright license

information on glucose levels, trends, and variations. Recent studies show that wearable sensors have a huge impact on improving glycemic control and hence, the complications related to diabetes. The monitoring results can be used for rule-based early diagnosis of diabetes [57] and the evaluation of its comorbidities in the context of internet-of-medical-things [32].

Apart from glucose monitoring, wearable sensors are still under development for the detection of other diabetes-related metrics. For example, Gao et al. conducted a study in [13] concerning the application of wearable electrochemical sensors in the monitoring of glucose levels in sweat. This non-invasive method exhibited highly correlated results with those obtained by blood glucose measurements, indicating its potential to act as an auxiliary tool in the management of diabetes.

Further integration of wearable sensors with mobile health applications and artificial intelligence has resulted in more innovative strides made in diabetes management [45]. Vettoretti et al. [53] describes how analysis using AI and wearable-sensor data can predict glucose trends and dosage advice for insulin. This new integration will enhance accuracy and open a holistic way of handling diabetic conditions, considering various factors such as diet, physical activity, and the level of stress. This continuous, real-time data allows for more accurate and highly personalized treatment strategies that help to improve the outcome of the patient. With advancing technology, it is expected that the integration of these sensors with AI and mobile health applications will further enhance the effectiveness and convenience of diabetes care.

12.4.2 Cardiovascular Diseases

Wearable sensors are a game-changing technology in the management of CVD due to continuous, real-time monitoring and personal health insights. Recent studies emphasize the potential for these devices to improve health outcomes through early detection, continuous management of the disease process, and further patient engagement.

State-of-the-art features, including electrocardiograms, photoplethysmography, blood pressure monitoring, and so on, are now being fitted into wearable sensors in the form of smartwatches and fitness trackers. These would provide a continuous monitoring system for vital signs, a very important function in patients who are suffering from CVD. For example, Pereira et al. [40] have reported that atrial fibrillation, generally preceding strokes, could be successfully identified by wearable ECG sensors, allowing timely medical intervention to prevent stroke.

Besides this, wearable sensors facilitate remote patient monitoring, hence eliminating frequent visits to the hospital. Heikenfeld et al. [18] have established that the incorporation of wearable sensors within telehealth systems has exhibited tremendous potential in the management of chronic conditions, including CVD, by continuously providing healthcare professionals with data that informs treatment decisions. This approach enhances not only patient convenience but also the optimization of healthcare resource utilization. This data can be integrated with machine learning algorithms to predict adverse cardiac events. Smuck et al. [48] focused on the application of artificial intelligence techniques in the analysis of wearable sensor data in a bid to predict heart failure exacerbations and facilitate pre-emptive interventions that might prevent hospitalization.

Another area in which wearable sensors play a very critical role is in the domain of patient engagement. Devices assist patients in taking an active role in managing their health through real-time feedback and encouragement of behaviour change. Anne-Noëlle Heizmann et al. [4] posit that the usage of wearable sensors presents an associated increase in PA levels and better adherence to the treatment regimen among patients suffering from CVD. Integration of these devices with healthcare systems might contribute to further revolutionizing the management of CVDs by achieving ultimately improved outcomes for patients and reduction in health costs.

12.4.3 Cardiometabolic Dysfunction

Miller [37] indicates that wearable devices are quite effective in monitoring the blood glucose of patients with diabetes. CGMs, worn on the surface of the skin, could support real-time analysis of glucose and aid both the patient and healthcare providers in swift dietary and insulin-related interventions. This closed-loop dependence has been shown to improve glycemic control and reduce hypoglycemia.

Wearable sensors are also indispensable for hypertension management. According to Hare et al. [17], wearable blood pressure monitors—the commonly integrated functionality into smartwatches and fitness bands—allow for the frequent tracking of blood pressure outside of clinics. Continuous monitoring enables the recognition of white-coat and masked hypertension, conditions frequently missed in a clinical environment, yet holding large cardiovascular risk implications.

In particular, wearable devices can track all relevant parameters of physical activity, heart rate variability, and sleep patterns that are important markers of cardiometabolic health. Rykov et al. [44] explain how such wearables could further track the intensity of physical activity with a high degree of accuracy and finally associate this with improvements in metabolic health markers, including BMI and lipid profiles. This data might be used to motivate patients toward lifestyle modifications and adherence to exercise regimens.

The implementation of wearable sensor data can enhance the functionality of telemedicine platforms. Health providers are transmitted real-time data for timely interventions and the formation of personalized treatment plans. This technology supports the shift from reactive to proactive healthcare that may reduce the burden of cardiometabolic diseases on healthcare systems. These sensors can therefore give a comprehensive management tool for cardiometabolic dysfunction based on their ability to detect, monitor, and treat these conditions early enough, providing personalized treatment by continuance of data in real-time [56]. Further improvement in this technology is highly likely to improve patient outcomes and bring efficiency to healthcare delivery.

12.4.4 Chronic Obstructive Pulmonary Disease

Wearable sensors have more rapidly come to the forefront in the management of chronic obstructive pulmonary disease, providing real-time monitoring of respiratory rate and pattern for tailored health care to patients [23]. Recent research has testified to their effectiveness in managing diseases and improving health outcomes.

A systematic review by Hussain et al. [19] highlighted the fact that wearable sensors could be able to predict acute exacerbations of COPD through changes in physiological patterns. As such, since these devices are predictive, it becomes possible to take preventive measures against admitted hospital cases and manage the disease more effectively. Since the devices will be used for predicting acute exacerbations, the system will help prevent admitted hospital cases as well as manage the disease effectively. Wearable sensors are one of the biggest advancements in COPD management and further studies are now needed to hone such technology and evaluate its long-term efficacy.

12.4.5 Parkinson's Disease

Wearable sensor technology has propelled the management of PD. These devices provide an opportunity for continuous, real-time monitoring of motor and non-motor symptoms providing valuable data and improving the quality of life in patients with the condition.

Wearable sensors, mainly accelerometers, gyroscopes, and EMG sensors, have been quite useful in the quantification process of the key motor symptoms of PD: tremor, bradykinesia, and postural instability. Rovini et al. showed, as recently as the [43] study, that through the use of inertial measurement units mounted at the wrist and on the ankles, identification and follow-up on tremors and gait anomalies can indeed be performed to establish non-invasive evaluation for disease progression and treatment efficiency. Especially, the electroencephalogram (EEG) signals can reflect the neural activities and be detected using wearable sensors. Some deep features associated with PD can be extracted from EEG signals and integrated with other multimodal data for diagnosis of PD [31].

The option of remote monitoring reduces the burden of frequent clinical visits and allows for the continuity of care which becomes especially crucial in the case of patients who are located in remote or underserved areas. In a study, Del Din et al. [11] reported that data captured on daily living activities by a wearable sensor system provided an objective and comprehensive basis for the design of patient-centred treatment plans with real-time medication management.

Besides the motor manifestations, wearable sensors are currently being researched for the monitoring of sleep disturbances and cognitive decline in patients with PD. In this respect, multimodal sensor systems can provide a holistic overview of the patient's condition, thus allowing multi-faceted treatment measures against the disease [38].

12.4.6 Huntingdon's Disease

Wearable sensors provide innovative ways in the management of Huntington's disease, a neurodegenerative condition associated with impairments in motor function as well as cognitive and psychiatric symptoms. Research underlines the potential use of wearable devices in an approach to monitoring and tailoring interventions to a more precise disease stage.

Subtle aspects of motor performance by subjects with HD can be captured, by wearable sensors like accelerometers and gyroscopes. These wearable devices monitor the patterns of moving and walking and show the objective measures of the motoric problem that would be otherwise unnoticed during clinical assessment. This is thereby doubly beneficial if this continuous monitoring translates into real-time adjustment of therapeutic interventions and possibly better patient outcomes [25].

Machine learning algorithms included in wearable sensors advance the analysis and interpretation capabilities of the sensors. This resonates with Batko et al. [6] which discusses how advanced analytics with sensor data could lead to better acquisition predictive modelling for the advancement of diseases. Such models will enable earlier intervention and more precise administration of treatment strategies to account for variability in disease manifestation from patient to patient. Wearable inertial sensors have a promising use in Huntington's disease because they provide real-time, objective data, improving monitoring and the individualization of treatment—very important in a disease diversified by its many symptoms and patterns of progression [52].

12.4.7 Alzheimer's Disease

Wearable technologies in Alzheimer's disease management today, make it possible to monitor a patient in real-time and deliver personalized care. The EEG features related with dementia and Alzheimer's disease can be detected using wearable sensors. Research evidence shows that wearable sensors could make a difference in the management of AD by continuously monitoring critical health parameters. According to Kourtis et al. [29], wearable sensors can capture subtle changes in daily activities and cognitive function, which generally precede the clinical symptoms of AD. With continuous monitoring of these parameters, caregivers and healthcare professionals could identify early signs of cognitive decline and take appropriate action.

The most important advantage associated with wearable sensors is their ability to provide data for individual treatment plans. According to a 2022 study by Mattison et al. [34], data collected from wearable devices could tailor such interventions at the individual level by slowing disease progression, which would improve the outcome of patients and reduce the burden on carers.

Wearable sensors also enable remote monitoring, which may be particularly beneficial in AD patients with severe mobility problems. As stated by Kourtis et al. [29], continuous assessment via wearables for remote monitoring improves the quality of life of patients, eliminating frequent visits to the hospital, and hence reducing the logistic burden of the conventional care approach.

Despite all these benefits, there exist challenges in the full-scale adoption of wearable sensors in the management of AD. The problems that it addresses range from the accuracy of the sensors to the user compliance to fully effect these devices [35]. However, if successfully integrated into AD care protocols, wearable sensors would greatly improve patient monitoring for early interventions and treatment strategy tailoring.

12.4.8 Chronic Venous Insufficiency

Wearable sensors are increasingly being used in the management of chronic venous insufficiency, a problem where poor blood flow to the veins in the legs is accompanied by pain, swelling, and ulcers. Recent developments in this line have been in the endeavour to design and implement wearable devices, acting as functions for continuous monitoring and management of symptoms for CVI.

Wearable sensors, in the form of smart socks or bands, can continuously monitor parameters such as venous pressure, blood flow, and limb movement. The use of devices employing technologies such as photoplethysmography and impedance plethysmography may facilitate the noninvasive evaluation of venous function. A research by Kim et al. [27] discusses how a wrist-worn PPG sensor could be used to monitor the changes in blood volume continuously, a clinical parameter in the management of CVI. It points out that wearable sensors can detect the first signs of blood insufficiency and provide timely feedback regarding therapeutic interventions.

A systematic review by Souza et al. [49] investigated the use of a smart wearable technology with embedded sensors, which tracked the activity of the lower limbs and gave real-time feedback on exercises for improving venous return. Their findings demonstrated that patient's compliance was improved by the real-time feedback and user-friendliness of wearable devices. Continuous data that are collected by wearable sensors allow for longitudinal assessment of CVI and give a full portrait of the course of the disease and treatment effect.

According to Souza et al. [49], health monitoring technologies have emerged as effective tools for the prevention, early detection, and management of chronic conditions', which can help in understanding the impact of lifestyle modifications and medical interventions on venous health for more effective and individualized patient care. These technologies, which have dramatically promoted the proactive management of CVI, potentially improve many health outcomes and quality-of-life qualities among patients.

12.5 Impact on Healthcare

Wearable sensors define a pivotal point for healthcare in managing chronic diseases; that would, by extending the frontier of the delivery of care, bring continuous monitoring and data-driven interventions to scale. These wearable devices hold the potential for massive, realized benefits because of real-time health data enabling timely detection with personalized treatment and obstacle-free patient engagement.

These sensors provide enormous levels of empowerment to the chronically ill by allowing them to monitor their existing health status continuously. They record vital signs during activities of daily living. This particularly helps in monitoring and controlling diabetes, hypertension, and cardiovascular conditions [3]. Continuous data flows will allow for timely interventions, thus giving opportunities to reduce the risk of severe health episodes. Patel et al. [39] have evidenced that real-time monitoring allows for a better clinical outcome by capturing the abnormalities before they become critical problems, contributing to the personalization of health care.

Data collected is analysed by a healthcare provider, who can then tailor the treatment plans to the needs of the patient. This individualized patient-specific approach increases the quality of care that patients receive and assures that they will get the most appropriate treatment for their condition [50]. For example, continuous glucose monitors used in managing diabetes help trace the details of the glucose trend, thereby giving accurate adjustments in diet, exercise, and medication. This improves not only glycaemic control but also the quality of life in general for patients [41].

Another area of significant impact for wearable sensors is patient engagement. Patients feel responsible and in control, empowered by the wearable devices, for the management of their health. The feedback from wearables can motivate patients toward a healthier lifestyle and enhance adherence to treatment by facilitating informed decisions about health options [24]. This proactive engagement helps ensure that people with chronic diseases maintain their long-term commitments to required lifestyle changes and adherence to their medication. The data generated by wearable sensors makes effective communication possible between the patient and the health practitioners. On the side of the clinicians, access to continuous and comprehensive health data would enable more precise decisions and modification of the intended treatment plans. This constant data inflow helps to fill the gap between regular check-ups and thus gives a truer and more holistic view of a patient's health status over time [16].

Baig et al. [5] note that this helps in successful chronic disease management by reducing emergency visits and hospital readmissions. Despite the several benefits, challenges to healthcare integration that wearable sensors pose are issues regarding data privacy and data management systems, as well as the accuracy and reliability of devices. Addressing these issues is therefore of essence towards the full realization of wearable technology potential in chronic disease management [1].

In summary, the advancement of wearable sensors has changed the prospects of the management of chronic diseases through the potential for continued health monitoring, treatment personalization, and an increased involvement of patients. These devices offer invaluable data that enable timely interventions, leading to improved clinical results. As technology improves further, the role of wearable sensors is likely to increase in healthcare, yielding more benefits to patients who have chronic conditions.

12.6 Trials and Developments

In the recent past, wearable sensors have changed the way chronic diseases are managed. These devices permit the continuous monitoring of vital signs and physiological parameters and allow for anomaly detection at an early stage with timely interventions [23]. Wearable sensors, through integration with mobile health applications and cloud-based platforms, make real-time data collection and analysis possible, increasing a healthcare provider's capability to make informed decisions based on the latest information about a patient [15].

Randomized controlled trials have shown that wearable sensors can enable better disease outcomes. Wearable cardiac monitors, however, have been able to successfully detect arrhythmia or some other cardiac event and thereby reduce the risk of stroke and other complications in patients with cardiovascular diseases as seen in [42].

Besides that, the development of sensor devices is getting more and more sophisticated and less intrusive. The newest technologies include flexible and stretchable sensors that attach to the skin and ensure comfort and usability [54]. Most of these sensors leverage cutting-edge materials and microfabrication techniques to deliver high sensitivity and specificity that help detect various ranges of biomarkers. For example, the materials for for sensing layer (photodetector) play a key role in improving the quality of PPG signal and its robustness against noises [33].

12.7 Overview of Technical Details

Wearable sensors have revolutionized modern healthcare by enabling major improvements in the monitoring and management of chronic diseases. Among these devices are glucose monitors, ECG patches, accelerometers, and smart textiles, all offering real-time data and actionable insight into a range of health conditions. Wearable sensors now imbibe sophisticated technologies such as AI, machine learning, and IoT, which revolutionize their functionality in terms of precision, hence making them very vital in personalized medicine.

Applications of wearable sensors in the management of chronic diseases are manifold. For diabetes, continuous glucose monitors provide better glycemic control. For cardiovascular diseases, wearable ECG monitors assist in the early detection of probably life-threatening arrhythmias. In COPD and Parkinson's, they track and manage symptoms, improving patient outcomes and in neurodegenerative diseases like Huntington's and Alzheimer's, wearable sensors could make a difference in monitoring the progression of the diseases and enable timely interventions. Table 12.1 discusses studies in relation to the chronic diseases and they suggest the positive impact of wearable technology in disease management and living a healthy lifestyle.

The effect of wearable sensors on healthcare extends beyond the benefits a patient derives to insights for bigger public health and reduced costs in healthcare systems. Further development and trials are underway to expand what such devices can do, promising even more integrated and responsive healthcare in the future. Wearable sensors thus, in a sense, stand at the very forefront of a healthcare revolution by empowering both patients and healthcare providers.

12.8 Discussion

Wearable sensors are at the heart of medical healthcare metamorphosis. The visually small devices are not only gadgets but miniaturised revolutions that are transforming the healthcare and lives of every individual on this planet. Wearable sensors are wonderful tools to effectively manage symptoms of chronic diseases by providing proactive and efficient healthcare interventions enabling the patients to live as comfortably as possible and independently.

Among these sensors, the ECG-based sensors are used for vital parameters related to the cardiovascular system which are crucial in detecting arrhythmia, and abnormal heart pressure which are very common symptoms of chronic heart diseases [7]. Respiratory sensors are useful in measuring rate of respiration and lung function which is crucial for patients with COPD [2]. Wristbands, cuffs and cuffless sensors are used for measuring blood pressure which is eminent for patients with hypertension [28]. PPG-based sensors, are versatile, inexpensive sensors that can be used for variety of conditions listed above. Glucose monitoring sensors can proactively monitor glucose level in bloodstream for patients that are in imminent danger of hyperglycemia or hypoglycemia. Lastly, orientation sensors like accelerometers and gyroscopes for measuring physical activity, sleep–wake cycle etc. All of these sensors enable continuous monitoring of vital signs and health indicators for various diseases that help in the detection of potential health issues, the data generated can be used for personalised treatment plans and assures medicine adherence of the patients.

Table 12.1 Summary of publications used in the chapter

Chronic disease	Title	Author	Method	Results and accuracy	Participants
Diabetes	Advanced Diabetes Management Using Artificial Intelligence and Continuous Glucose Monitoring Sensors	Vettoretti et al. [53]	Development and validation of AI-based predictive models aimed to forecast, in real time, the blood glucose levels. Data is then analysed from participants wearing CGM sensors that allowed them to monitor their glucose levels continuously. The AI models were trained and validated on this data to make predictions of future glucose levels more accurately	The AI model resulted in strong predictive capabilities, with the ability to accurately forecast glucose levels up to 30 min in advance, with high accuracy, with the results indicating a significant improvement in glucose level forecasting compared to traditional methods	Participant cohort with diabetes, with CGMs
Cardiovascular diseases	The emerging clinical role of wearables: factors for successful implementation in healthcare	Smuck et al. [48]	Review of existing literature and case studies on wearable technology in healthcare. Analyzed various factors affecting the adoption and effectiveness of wearables, including technological, clinical, and organizational aspects	The review did not involve direct experimentation with participants but relied on existing studies and case reports to assess the accuracy and effectiveness of wearable devices. The accuracy of the devices was discussed in terms of their ability to reliably measure health metrics and provide meaningful data for clinical decision-making	None as uses various different studies rather than a single individual study

(continued)

Table 12.1 (continued)

Chronic disease	Title	Author	Method	Results and accuracy	Participants
Cardiometabolic dysfunction	Novel Digital Technologies for Blood Pressure Monitoring and Hypertension Management. Current Cardiovascular Risk Reports	Hare et al. [17]	A comprehensive review on digital health innovations such as wearable devices, smartphone applications, and remote monitoring systems. Analysed the methods used and their integration with healthcare systems, and their potential to improve patient outcomes	Resulted in finding a number of technologies to accurately monitor blood pressure and manage hypertension, enabling early detection of hypertension and better patient adherence to treatment The accuracy depended on device and method used, some showed high accuracy comparable to clinical-grade equipment, others needed further validation	Included studies that involved various populations, with participants ranging from healthy individuals to those diagnosed with hypertension
COPD	Wearable Sensors for Respiration Monitoring: A Review	Hussain et al. [19]	Extensive literature review of current wearable sensor technologies for monitoring respiration. The review includes an analysis of the types of sensors, principles, materials and methods. The study synthesizes data from various experimental studies and clinical trials	Wearable respiration sensors have shown significant promise in various applications, including health monitoring. The accuracy of the sensors reviewed varies widely, with some studies reporting accuracies as high as 95% in controlled environments	Studies used typically involved small sample sizes in controlled environments, which may limit the generalizability of the findings

(continued)

Table 12.1 (continued)

Chronic disease	Title	Author	Method	Results and accuracy	Participants
Parkinsons disease	Free-living monitoring of Parkinson's disease: Lessons from the field	Del Din et al. [11]	Evaluates the effectiveness and challenges of using wearable sensors to monitor Parkinson's disease in real-world settings. Participants wore accelerometers and gyroscopes for continuous data collection over extended periods. These sensors were used to capture various movement-related parameters such as gait and tremor	Data collected was useful for understanding symptom variability and the impact of treatment over time. Study identified several challenges, including data management issues, the need for robust data analysis methods, and the importance of user compliance. The study reported that wearable sensors demonstrated a reasonable level of accuracy in detecting motor symptoms when compared to clinical assessments. However, it also pointed out that while wearable technology could provide valuable data, it was not always perfect and had limitations that needed to be addressed for more precise and reliable monitoring	Diverse cohort of 20 participants

(continued)

Table 12.1 (continued)

Chronic disease	Title	Author	Method	Results and accuracy	Participants
Huntingdon's disease	Using Wearable Sensors and Machine Learning to Assess Upper Limb Function in Huntington's Disease	Vaziri et al. [52]	The upper limb function was monitored during daily activities using a wrist-worn wearable sensor, called PAMSys ULM, over seven days, with an average daily compliance of 99%. Goal-directed movements (GDM) of the hand were detected using a deep learning model, and kinematic features of each GDM were estimated. The collected data was used to predict disease groups and clinical scores using a combination of statistical and machine learning-based models	The results indicated significant differences in the number of GDM counts between individuals with HD and CTR participants. Acceleration-related features differed significantly between HD and CTR groups. The study had a balanced accuracy of 67%	The study included 16 participants diagnosed with Huntington's disease, 7 prodromal participants and 16 controlled participants

(continued)

Table 12.1 (continued)

Chronic disease	Title	Author	Method	Results and accuracy	Participants
Alzheimer's disease	Digital Biomarkers for Alzheimer's Disease: The Mobile/ Wearable Devices Opportunity	Kourtis et al. [29]	**A comprehensive review** and analysis of wearable technologies that could be used to track and assess behavioural, cognitive, and physiological parameters in relation to AD	The results suggest that these devices hold significant promise for the early detection and monitoring of AD. The level of accuracy varied among different devices, with some showing strong correlations with clinical assessments and others being less reliable	The participants ranged from small clinical cohorts to large and diverse groups
Chronic venous insufficiency	Smart Wearable Systems for the Remote Monitoring of Selected Vascular Disorders of the Lower Extremity: A Systematic Review	Souza et al. [49]	A Systematic Review of studies that included the use of smart wearable devices for monitoring conditions such as peripheral arterial disease, deep vein thrombosis, and chronic venous insufficiency	The review concluded the potential of these systems to improve remote patient monitoring, but also noted the need for further research to enhance their accuracy and reliability	Participant demographics varied widely across the studies from healthy individuals to patients with a diagnosis

The evolution of wearable sensors went hand in hand with advancements in MEMS and communication systems for sensors. The MEMS technology enables the integration of small components like accelerometers, magnetometers, sensors for heart rate, piezoelectric sensors and various light-based sensors, detectors and processing units on a single chip. BLE data transmission ensures data transmission reliably and accurately as this data is crucial for monitoring. Such devices, given their small size and low power consumption can be used for extended periods of time. The applications of big data, machine learning and AI have enabled advanced and complex data analysis possible in real-time.

Wearable sensors have grown increasingly important in managing various chronic health conditions, providing continuous monitoring and valuable insights into patient health. Wearable sensors for glucose level monitoring can provide better dosage and dietary control. The activity and orientation sensors have been used for people with Parkinson's and Huntington's disease, providing better gait and movement control and precise drugs the patients need. PPG, ECG, temperature and other sensors are used for better cardiovascular health indicators and to monitor various metabolic disorders. These sensors have enhanced telemedicine platforms for patients where frequent hospital and healthcare provider visits are inconvenient.

Wearable sensors can provide real-time data on the physiological parameters of interest thus enabling us to detect anomalies early and manage chronic conditions timely and effectively. These sensors can collect large amounts of data about health metrics of individuals therefore wearable sensors help to design personalised treatment plans for chronic conditions. This not only enables patients with chronic diseases to play an active role in managing their health but also to live independently. This data can be analysed to gain insights into disease progression and the efficacy of treatments. This also helps researchers to refine and develop interventions for these diseases, detect early signs of health deterioration for the patients and take preventive measures.

Although wearable sensors hold a lot of potential for the management of chronic diseases, there are also challenges associated with them. Some of the challenges that may be faced are issues of data privacy, standardization, and long-term adherence as shown in Fig. 12.4. Firstly, the user comfort and miniaturization are important considerations for long-term multifunctional monitoring. Secondly, the data from different cohorts can be heterogeneous [10]. For many wearable sensors, there is gap in large-scale validation. Thirdly, real-time processing of multimodal data poses a new challenge for algorithms, with an increasing need for cloud-based, AI-enhanced data processing frameworks. Finally, the data privacy, regulatory issues, and unbiased, equitable access are unaddressed ethics concerns [46]. Despite these limitations, progress made toward this end underlines a future where wearable technology assumes a place at the heart of proactive, personalized health care.

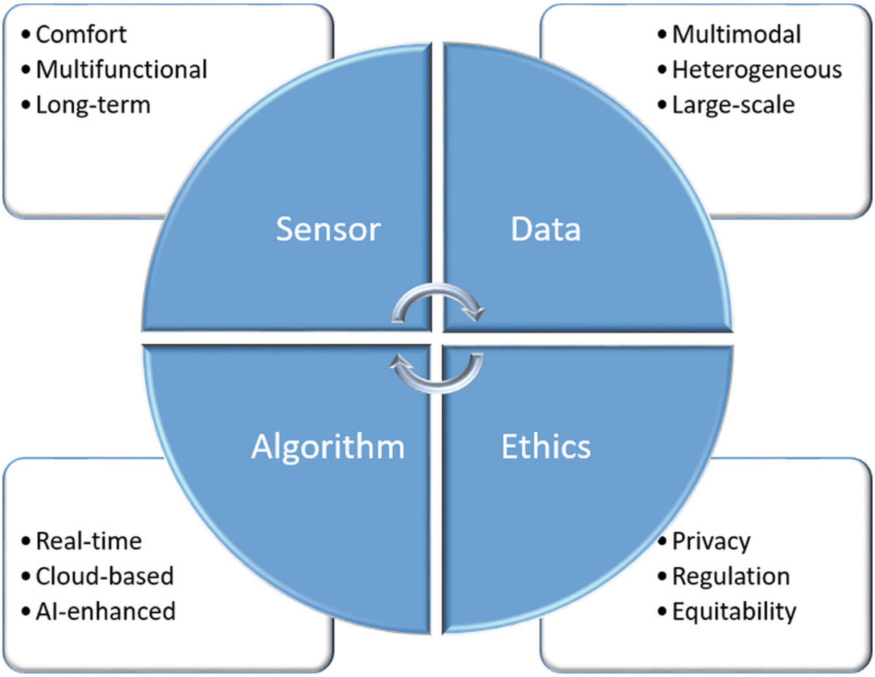

Fig. 12.4 Unmet challenges in wearable sensors

12.9 Conclusion

Despite challenges related to sensor, data, algorithm, and ethics, wearable sensors have transformed chronic disease management and are thought to play an increasingly significant role in healthcare as technology continues to advance. The future of wearable technology seems promising, with significant advancements on the horizon that will further integrate these devices into healthcare delivery. The combination of AI and mHealth applications has capacities to make healthcare more accessible, proactive and personalised. However, to fully realize the advantages offered by wearable sensors, we need to overcome the concerns related to the privacy of data, accuracy, engagement of users, interoperability, and legal and ethical considerations. As research and development continue in the area of wearable sensors, it will likely become a key tool to improve health outcomes.

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Chapter 13
Radio Frequency Sensing for Detecting Activities of Daily Living

Behzad Ali Shah, Syed Aziz Shah, and Haipeng Liu

Abstract This chapter gives an in-depth review of RF sensing technology for Activities of Daily Living (ADL) monitoring, emphasizing elderly care. It aims to assess recent advancements in AI-driven for monitoring of ADL systems and discuss the integration of various sensor categories, illustrating the short-comings and difficulties of existing monitoring for ADL, such as accelerometers and gyroscopes in smartwatches. The study investigates RF sensing techniques, such as Wi-Fi-and radar-based devices, highlighting how they might be used to identify early health risks and record distinctive human movement patterns. The paper emphasizes how advanced Machine Learning (ML) algorithms are used with RF sensing to increase the accuracy of ADL. It tackles practical implementation issues such as reliable system requirements data protection and user acceptance. To help researchers improve methodology and handle identified difficulties, an extensive review of the latest developments, possible future directions of monitoring for ADL, and an overview of present systems are provided.

Keywords RF sensing · Software-defined radio · Radar · Machine learning

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13.1 Introduction

The issue of monitoring the health of the elderly population has received increasing attention in recent years. Even small problems with carrying out daily duties might put senior adults at great risk and have serious long-term effects. The World Health Organisation (WHO) estimates that over 686,000 deaths globally each year result from accidental injuries, with activities associated with daily living playing a significant role in the overall health and safety of older adults [1]. Adults older than 65 years of age are particularly vulnerable, as their ability to perform various ADLs reduces, exposing them to a higher risk of injuries or mishaps. In low- and middle-income nations, where healthcare services and monitoring options may be scarce, over 80% of injury-related deaths take place. Furthermore, problems in ADLs often result in non-fatal injuries, which can negatively influence the quality of life for older adults.

According to estimates from the World Health Organisation, 37.3 million injuries resulting from ADLs and other daily tasks require medical attention annually [1]. Reduced mobility can have a variety of negative effects, from minor injuries to more serious health issues like fractures and brain trauma. As the world's population ages, chronic illnesses and physical weakness are becoming more common. Therefore, in elderly care, efficient ADL monitoring is important. By detecting possible threats and offering immediate assistance via intelligent monitoring systems, the burden on global healthcare systems can be greatly diminished. The United States alone incurred medical costs exceeding 50 billion dollars in 2015 due to accidental harm while carrying out routine activities [2].

Healthcare costs associated with ADL monitoring are expected to rise in parallel with the aging population. The purpose of monitoring systems is to detect unusual occurrences, like abrupt alterations in behavior or mobility, and promptly alert relatives, caretakers, or emergency services. For instance, people suffering from dementia, who display disorientation and memory loss, may wander or have accidents while going about their regular activities. The risk of harm during ADLs is increased in approximately 67% of these individuals due to their propensity for wandering behaviors [3]. Elderly people who are weak or immobile may experience discomfort and health issues as a result of prolonged immobility. Moreover, conditions including epilepsy, narcolepsy, and sleep apnea interfere with everyday activities and make them harder [4].

Researchers have started creating smart monitoring systems, especially for in-home elder care, to address these issues. Such systems make use of a variety of sensors, such as pressure sensors, cameras, and RFID tags incorporated into furniture, clothing, and other household items. RFID tags communicate with readers positioned throughout the house to monitor ADLs and ensure that senior citizens are safe [5]. Furthermore, body area network (BAN)-based devices are being developed. These systems consist of several nodes containing sensors that monitor movements and provide information to detection devices or a smartphone [6].

Radar technology presents a promising, non-invasive method for monitoring ADLs, as it preserves privacy, operates through walls, and detects human movement under various conditions. By analyzing radar emissions and their relationship to human gait and movement, monitoring systems can effectively track ADLs and alert caregivers to any concerning changes [5]. For elderly individuals to perform ADLs safely, maintaining stable posture and movement is crucial. Gait stability is influenced by several factors, including muscle fitness, cognitive function, and fear of injury [7].

Integrating Radio Frequency (RF) sensing into the detection of ADLs represents a novel and essential development in elder care. As the global population ages, the demand for such advanced monitoring systems will continue to grow, making this a pivotal area for future research and innovation.

13.2 Related Work

This section outlines the various methodologies and technologies for monitoring of ADLs demonstrated in previous studies. Noury et al. [8] focus on the mechanics of ADL detection methods and evaluation using statistical analysis. They examine diverse analytical methods, including velocity thresholds in sensor readings, no movement detection, and inversion in acceleration vector polarity. Xinguo [9] concentrates on ADL detection fundamentals, particularly for the elderly, categorizing methods into wearable, ambient, or vision-based devices. This categorization is further divided based on motion, alignment, closeness, structure, and three-dimensional head position analysis.

Perry et al. [10] categorize real-time techniques into three groups: those measuring acceleration, those combining acceleration with static orientation and gyroscope data, and those specifically for ADL detection events. Hijaz et al. [11] discuss ways to use everyday activity monitoring to identify ADLs and erratic movements in elderly people. These approaches may be divided into three categories: kinematic sensors, audio and ambient sensors, and video analysis. Mubashir et al. [12] review various ADL detection systems and algorithms, dividing methods into wearable, ambiance, and camera-based devices, further classified based on accelerometry, pose modeling, audio/visual ambiance detection, posture analysis, and more.

Delahoz and Labrador [13] offer a qualitative analysis of ADL detection and prevention systems, classifying sensors as wearable or external. The latter are further subdivided into systems that rely on ambient light or vision. In addition, they examine the temporal complexity of several classification methods, including decision trees, K-Nearest Neighbour, and Support Vector Machine (SVM), and explore features of ML such as feature extraction, building, and selection. They address ADL risk elements that are environmental, psychological, and physical, and they draw attention to design issues including cost, energy consumption, privacy, and obstructiveness. Schwickert et al. [14] systematically review wearable-sensor-based ADL detection systems, examining research on both artificial lab-recorded ADL events and real-life spontaneous ADLs.

Zhang et al. [15] focus on studies using vision sensors, presenting datasets on ADL detection, and classifying vision- based approaches with RGB or 3D depth cameras. Pannurat et al. [16] concentrate on automatic ADL detection systems, categorizing current platforms into wearable and ambient devices and dividing classification techniques into rule-based and machine-learning algorithms. They also evaluate various ADL detection products in terms of size, weight, sensor type, battery, operational functions, and future developments.

Igual et al. [17] review 326 ADL detection papers, classifying them into wearables (such as cellphones) and context- aware systems. Components such as microphones, pressure and infrared sensors, cameras, and other components are used to categorize context-aware systems. Ward et al. [18] examines methods of ADL detection based on usage and technological implementation, classifying devices as manually operated devices, body-worn automatic alarm systems, and devices identifying possible alterations that might indicate an ADL event.

Li et al. [19] used a multi-sensor approach, combining radar and wearable devices, to improve activity classification accuracy. In their study, a 5.8-GHz frequency-modulated radar sensor was used in an office environment with ten volunteers performing various activities. This approach increased accuracy from 80 to 98%.

An FMCW (frequency modulated continuous wave) radar system was used in a controlled laboratory environment to monitor four everyday human movements: standing, walking, falling, and sitting. Over time, each activity creates distinct micro-Doppler signatures, as shown in Fig. 13.1. Participants were instructed to perform the tasks within the sensing zone of the radar system, which had fixed transmitter and receiver antennas. The resulting spectrograms clearly show how different motions affect the Doppler frequency spread. For instance, walking produces rhythmic bursts, while falling results in an abrupt, intense frequency shift. This radar-based method offers a contactless, private way to monitor daily activities and has great potential for applications such as smart home security and fall detection in senior care.

Luque et al. [20] provide a comparison of ADL detection systems based on Android, with an emphasis on predefined thresholds or ML (pattern matching). Casilari et al. [21] explore techniques for Android devices to detect ADLs, comparing various algorithms in previous studies regarding system design, sensors used, methods, and false alarm responses.

Khan and Hoey [22] review ADL detection approaches from a data availability perspective, dividing these into classes based on the sufficiency of training data, regardless of sensor methods for feature or type extraction. Casilari-Pérez et al. [23] examine how artificial neural networks (ANN) are utilized in ADL detection systems with wearable sensors, classifying techniques using ANN classifier characteristics.

Finally, [24] another research classifies works based on utilized approaches and accomplishments after conducting a thorough evaluation of publications, projects, and patents on ADL prediction, detection, and prevention globally. Ribeiro et al. [25] propose an IoT-based solution for homes, hospitals, and elderly care facilities, using a three-layer processing architecture with edge, fog, and cloud. To classify human

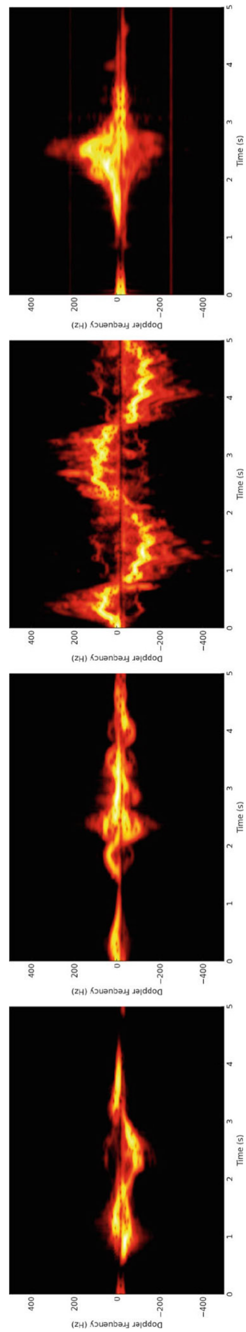

Fig. 13.1 Micro-doppler spectrograms of human activities: sitting, standing, walking, and falling

ADLs, they use and compare an ANN model with a mathematical model based on the morlet wavelet. They discovered that combining the two models yields a high accuracy of 92% with no false negatives.

In the Table 13.1 the principles, applications, benefits, and drawbacks of several sensors used to monitor respiratory movements, body movements, and falls are highlighted. There are basically two types of sensors contactless and contact- based (wearable).

Wearable sensors like Photoplethysmography (PPG), Accelerometer and Gyroscope, Strain Gauges, and Inkjet-printed strain gauges [26–28] are often used for monitoring respiratory movements and posture. These sensors are miniaturized, low-cost, and suitable for continuous monitoring but are sensitive to motion artifacts and require proper placement to be effective. For example, PPG is sensitive to motion artifacts, while accelerometers are prone to posture-related inaccuracies. Distance-based magnoelectric/capacitive sensors and Piezoelectric sensors are non-invasive and comfortable for the wearer, making them ideal for both respiratory and body movement monitoring. However, their accuracy can be affected by posture changes or external vibrations.

Airflow pressure sensors and Triboelectric nanogenerators (TENG) [29] are designed to capture respiratory changes, with airflow sensors being highly accurate for nasal breathing but uncomfortable for long-term use. The triboelectric nanogenerators show promise for monitoring movements and falls, although further evaluation is needed.

Non-contact methods such as Ultra-Wideband (UWB) Radar Sensors [30, 31], Camera-Based Respiration Monitoring, and WiFi-based Channel State Information (CSI) monitoring provide advantages for body movement and fall detection. UWB radar and camera-based systems, for instance, offer high accuracy without needing to be in direct contact with the body, making them suitable for seated or resting patients. However, these methods require careful calibration and can be affected by environmental noise. The WiFi-based monitoring method is cost-effective and non-intrusive but may struggle with distinguishing different types of movements due to environmental variations.

These systems are crucial for developing advanced health monitoring technologies, particularly for elderly care, where continuous movement and respiratory monitoring are essential.

13.3 RF Sensing Technolgies

This part offers an overview of the most prevalent, affordable, and reliable non-contact RF technologies used in contributed living and healthcare, such as radar-based and Wi- Fi-based systems.

Table 13.1 Comparison of wearable sensor with contactless sensors

Type	Sensor	Principle	Applications in Movement Monitoring	Advantages	Limitations
Wearable	Photoplethysmography (PPG)	Optic pulse wave	Respiratory movement, pulse wave	Can be miniaturized, low cost	Sensitive to motion artifacts
Wearable	Accelerometer and Gyroscope	MEMS acceleration	Respiratory movement, body movement	Low-cost, reliable for posture detection, minimal invasiveness	Sensitive to posture and motion artifacts
Wearable	Strain Gauge	Strain variations during local body movement	Respiratory movement	High accuracy in clinical settings	Requires contact, motion artifact can affect accuracy
Wearable	Distance-based magnoelectric/ capacitive sensor	Changes in magnetic field, electrical resistance, or capacitance caused by distance	Respiratory movement, body movement	Non-invasive, comfortable to wear	Sensitive to variations in body posture and volume changes
Wearable	Piezo-electric/resistive sensor	Piezoelectric effect from body movements	Respiratory movement, body movement	Durable, can work under physical strain	Affected by external vibrations and strain
Wearable	Inkjet-printed strain gauge	Variations in resistance with respiration	Respiratory movement	Accurate, wearable, stretchable, and inexpensive	Sensitivity to incorrect placement and posture
Wearable	Airflow pressure sensor	Air pressure changes during respiration	Respiratory movement	High accuracy for nasal breathing	Uncomfortable for long-term use

(continued)

Table 13.1 (continued)

Type	Sensor	Principle	Applications in Movement Monitoring	Advantages	Limitations
Wearable	Triboelectric nanogenerator (TENG)	Electric energy generated during movement	Respiratory movement, body movement, falls	Self-powered, lightweight and flexible, high sensitivity, durable	Sensitive to environmental conditions, mechanical impact concerns, durability challenges under heavy strain
Contactless	Camera-Based Respiration Monitoring	Optical detection of chest movement	Respiratory movement, body movement, falls	Non-contact, useful for seated patients	Limited to specific postures, low accuracy with movement
Contactless	Ultra-Wideband (UWB) Radar Sensor	UWB Radar using Doppler Effect	Respiratory movement, body movement, falls	Non-contact, high accuracy, tracks multiple movements, reliable even at distance	Sensitive to environmental noise and requires careful calibration
Contactless	USRP-based SDR (Software-Defined Radio)	Detects changes in Channel State Information (CSI) using RF signals	Respiratory movement, body movement	Non-contact, portable, detects small-scale movements, flexible	Sensitive to environmental noise, requires careful calibration
Contactless	WiFi-based CSI monitoring	Uses WiFi signals to monitor body movements and analyze signal reflections	Body movement, falls	Non-intrusive, utilizes existing WiFi infrastructure, low-cost	Sensitive to environmental changes, limited accuracy in distinguishing different types of movements

13.3.1 Radar-Based Detection Systems

A transmitter that emits electromagnetic (EM) signals, antennas for sending and receiving (often the same antenna is used for both), a receiver, and a processor for data analysis are the main components of a RADAR system, which stands for Radio Detection and Ranging. When objects reflect, or backscatter, radio waves generated by the transmitter, details about their identification, range, velocity, and trajectory can be obtained [32]. Object velocity is estimated using the doppler effect, which involves measuring changes in the radar signal's carrier frequency. By examining an object's micro-doppler signature, one can figure out its identification. These fingerprints are minute variations in the backscattered radar signal brought on by tiny rotations or motions within the object [33]. In human monitoring, these micro-doppler signatures correspond to specific movement patterns of the torso, limbs, and head. These patterns are unique to individuals and specific activities, making them highly effective for automatic classification and monitoring purposes.

A variety of short-range radar systems, including frequency- modulated continuous-wave (FMCW), pulsed radar, ultra- wideband (UWB) radar, and CW radar, have been developed for various applications [34–36]. These radars are often categorised based on their operating frequencies, such as C-band, X-band, K-band, etc. Another key aspect of radar sensing is directivity, which is largely determined by the design and structure of the antenna. However, the basic sensing principles are generally the same across different radar types. Data from radar sensing may be used to ascertain the location, speed, and other characteristics of an object. After this data is demodulated using certain techniques, it is stored as carriers or matrices. For example, instead of looking at every point in the time series, the focus may be on extracting signal properties like amplitude, phase, and frequency when analysing a sequence of sinusoidal signals over an extended period [37]. Both statistical and multi-domain data can be retrieved. The variance, standard deviation, and mean are examples of common statistical characteristics. There are more popular methods for extracting information, which we shall cover later.

Radar systems are typically categorised into two main classes.

(1) ***Active Radar***: Systems that include a separate transmitter and receiver that may be combined into one device are known as active radars [38, 39]. To broadcast radar wave- forms, this arrangement requires certain gear and access to the accessible RF spectrum. Active radars have the important benefit of having complete control over the emitted signal's characteristics. The radar signal's time-of-flight throughout its passage from the transmitter to the target and back to the receiver is used to calculate the existence and distance of objects.

(2) ***Passive Radar***: Unlike active radar systems, passive radar systems lack a specific transmitter. Rather, they employ an already-existing transmitter as a signal source, such as a DVB-T or Wi-Fi system [40, 41]. The advantage is that they don't require a specific spectrum allotment and only require simpler technology. The lack of control over the broadcast waveform, meanwhile, is a significant drawback and might not be suitable for the best radar performance. By timing the difference between the direct signal from the source and the signal echo reflected off objects, these systems can detect the existence and distance of objects [42].

In radar-based RF sensing, whether active or passive, the signal processing begins with an experimental dataset, as shown in Fig. 13.2. To increase the size of the dataset, this dataset may contain measured data, data from kinematics or numerical models, or

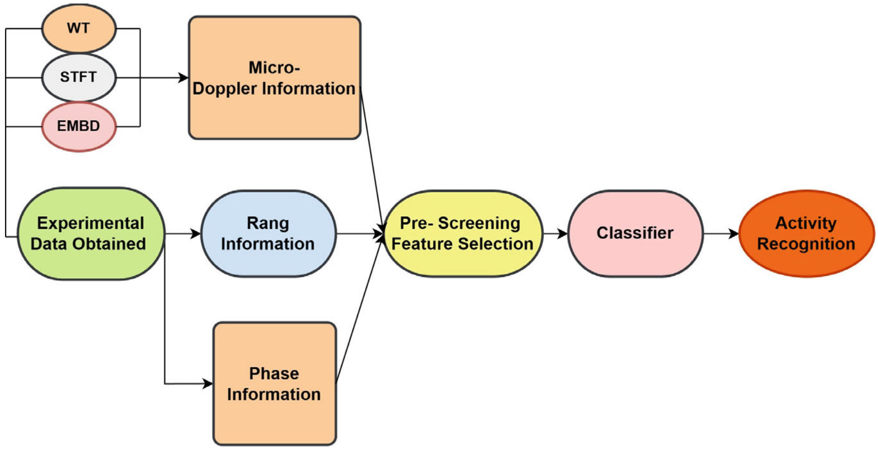

Fig. 13.2 Data analysis in radar systems for human activity recognition

a combination of the three. The data undergoes processing to extract range, phase, or micro-doppler information. Techniques like Wavelet Transform (WT), Short- Time Fourier Transform (STFT), or Extended Modified B- Distribution (EMBD) are used, particularly for extracting micro-doppler information, often used in ADL classification [43]. Yet, range and phase data can also provide valuable insights. The next step involves extracting numerical features from the data for use in a classification algorithm. To enhance performance and reduce false alarms, data pre-screening and feature selection are employed to pinpoint the most pertinent data or feature subset. For example, in monitoring parkinson's disease patients, this step could identify the start and end of a freezing of gait (FOG) episode by analysing movement speed. The data collected during this period is then used to extract specific features.

Ultimately, these characteristics are fed into ML classifiers, which employ a portion of the data for training and the remaining portion for efficacy testing. Numerous categorization techniques, such as SVM, k-nearest neighbours, random forests, and deep neural networks, have been applied, each with varying computing complexity. Typically, a combination of measures, including accuracy, sensitivity, specificity, and others, is used to evaluate their efficacy [44]. It's important to remember that many classification algorithms assume that the input feature samples are uniformly distributed. This assumption may not always hold for data about various human activities, as individual acts might be impacted by past and present behaviours.

13.3.2 Wi-Fi-Based Detection Systems

When a person moves within a certain area, they disrupt the wireless signals, altering signal paths, weakening the signal, and causing frequency shifts [45]. These movements create unique changes in the wireless channel information (WCI) [46, 47], which describes how RF signals are affected by human movement. This concept is used in healthcare research with common devices like Wi-Fi routers and network interface cards in computers.

Similar to radar-based systems, Wi-Fi-based activity recognition data collection and processing includes data capture, signal processing, and motion detection categorization as shown in Fig. 13.3. Most Wi-Fi technology can assess wireless channel conditions and signal strength, but performance can be impacted by signal reflections, refractions, and scattering. Different Wi-Fi system types are used to identify various human activities. The technologies and techniques used by these systems to record and examine wireless signals vary.

(1) ***Software-Defined Radio (SDR) Systems***: SDR systems process the signals that radio hardware receives using software. More advanced signal analysis and the customisation of detection algorithms are made possible by this flexibility [48]. SDR systems are versatile tools that can be utilised for a variety of research and application uses. They are capable of detecting a broad range of activities.
(2) ***Received Signal Strength Indicator (RSSI)-Based Systems***. Wi-Fi signals provide signal strength indicators (RSSI) [49] that can identify various human activities. However, RSSI struggles with detecting subtle movements like breathing and heartbeat due to noise and limited resolution. WCI, in contrast, can detect smaller movements by analysing distinct channels of frequency.
(3) ***Channel State Information (CSI)-Based Systems***: Systems based on CSI offer comprehensive details about the wireless channel, such as the phase and amplitude of transmissions on various subcarriers [50]. This makes it possible to identify different human activities more precisely and to detect smaller motions, including breathing and heartbeat. The Intel 5300 network interface card, which

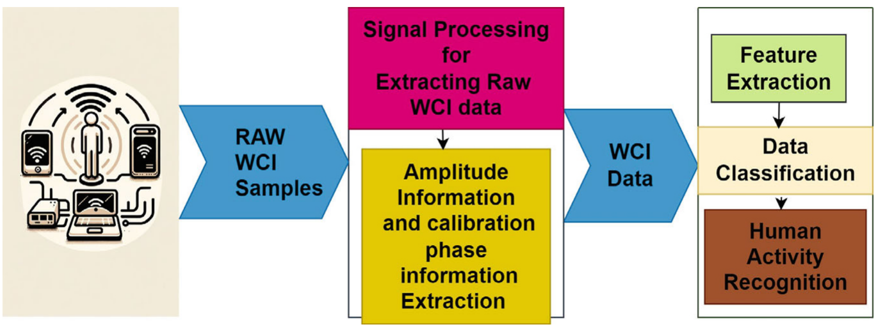

Fig. 13.3 Basic framework for a Wi-Fi-based system for recognizing human activities

is used to capture WCI data, is one example [51]. WCI is superior to RSSI because it enables in-depth examination of certain subcarriers. These network cards enable computers to continually receive WCI data.

However, raw phase data is often random and must be refined for practical use. By continuously or periodically measuring WCI, we can track changes in a person's position, direction, and angle of arrival of signals, as human presence and movement disturb the wireless channel over time. Each human motion creates a unique WCI pattern based on amplitude variations. After selecting a particular subcarrier for analysis, ML algorithms employ the improved phase and amplitude data to categorise various bodily motions [51].

(4) ***Orthogonal Frequency Division Multiplexing (OFDM)-Based Systems***: Multiple frequency channels are used by OFDM-based systems to deliver data simultaneously [52]. OFDM-based systems are able to distinguish between various sorts of activities and detect precise motions by examining the changes in these channels.It gathers amplitude and phase information from numerous subcarriers using symbols from orthogonal frequency division multiplexing (OFDM) [53].

13.4 Radar Technology for ADL

Activity recognition and gait analysis are critical in remote health monitoring, enhancing life quality, and enabling personalised treatments. They provide continuous medical data for better patient assessment, reduce healthcare costs, and facilitate prompt responses to emergencies [54]. Radar sensing technologies can identify various gaits by analysing range, doppler, amplitude, and phase data [55]. This capability allows for the detection and categorization of everyday activities, like walking, sitting, and standing, and crucial events such as falls [56] which will be explained in a separate section.

Regular engagement in these activities can indicate good health, while deviations might signal health deterioration. To identify inside activities using radar technology, a variety of approaches, including RF sensing, artificial intelligence, ML, and deep learning, must be integrated. The primary uses of radar in healthcare are detailed in Fig. 13.4. There are several uses for radar sensing in the medical field, particularly in the continuous monitoring of people within its range [57]. This includes ongoing observation of chest movements and heartbeats, which are crucial in fields like safety, security, the military, and healthcare. There have been several studies focused on accurately measuring respiration rates and vital signs, which are key indicators of a person's health [58, 59]. However, detecting other body movements, such as the orientation of the human body, remains challenging.

The phase information from Doppler radar correlates with chest movements, and the signal strength reflected by the human body varies depending on how the radar waves interact with it. The doppler Radar Cross Section (RCS) is a useful tool for

Fig. 13.4 Radar-Based recognition of activities in healthcare

characterising the total signal backscattered by moving body components [60, 61]. RCS is dependent on the physical area of the breast, the reflectivity of the surface, and the directivity of the radar at a particular frequency. Moreover, the RCS is influenced by various types of body movements, the human body's asymmetry along vertical axes, and the chest's orientation relative to the horizontal or vertical axis. The positioning of the transmitter-receiver pair also affects the RCS [62]. Several healthcare applications of radar technology are explored in more detail in the following sections.

13.4.1 Recognizing Position on a Bed

A simple yet effective method for detecting sleep positions on a bed was demonstrated in a study. This research focused on identifying different sleeping positions using the RCS. It was observed that the RCS from a person's backside is roughly nine times higher than from their front. The in-phase (I) and quadrature (Q) components of the back-scattered signals are illustrated in Fig. 13.5 [63] of the study. To exclude the direct current (DC) component and precisely estimate the RCS, the complicated value matrix was split into many parts, each encompassing a complete respiration cycle. The radius of each arc in these segments was then determined using a centre approximation method, as described in another study [64].

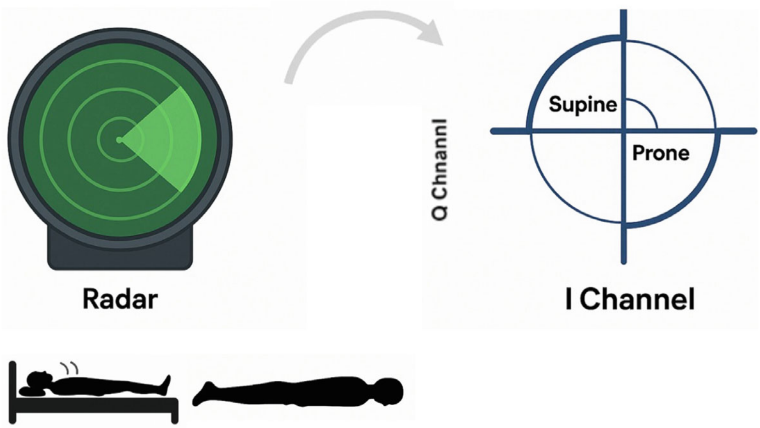

Fig. 13.5 Detection of a person breathing in supine position and respiration rate monitoring in prone position

13.4.2 Patients Affected by Sleep Disorders

Unusual sleeping patterns are common in patients with sleep disorders, and these can result in problems with emotional, physical, and mental health [65]. There are various types of sleep disorders, and one common method to study and monitor these conditions is polysomnography (PSG) [66]. PSG monitors heart rates (ECG), brain activity (EEG), eye movement (EOG), and muscle activity (EMG). However, this approach is cumbersome, expensive, and difficult for tracking aberrant sleep events since it necessitates that patients spend the night in a specialised facility and use wearable sensors.

The physiological monitoring radar system (PRMS), a noninvasive device, was created to overcome these difficulties [67]. This more comfortable and economical method effectively tracks a person's sleep pattern. CW radar is used by the PRMS to detect situations such as sleep apnea in real-time.

13.4.3 Unique Individual Identification

Each person breathes differently, with variations in things like the direction of expiration, the movement of the lungs as a result of air intake, and the tidal volume. Individual breathing patterns can differ depending on several elements [68], such as the neurological system or electrochemical loops, regardless of whether they are resting, normal, or pathological. These patterns, when recorded in ventilatory chambers, present a specific airflow and ventilatory profile for each person [69]. When data from hundreds of individuals is collected over time, these unique breathing profiles can potentially be used for individual identification, offering an alternative to traditional fingerprinting methods. Rahman et al. [69] presented a distinctive personal identification system that uses a CW radar system to identify people using their vital signs.

Identifying multiple individuals in an indoor setting with a radar system is quite challenging [70]. However, by using multiple antennas in the radar setup, the sensor may be able to count and differentiate people based on their unique cardiovascular patterns or simply detect life in a designated area. Occupancy monitoring with radar can be achieved by analysing heart rates [71]. It is feasible to differentiate between people even when their heart rates are comparable by employing methods such as the angle of arrival in conjunction with a single antenna arrangement, multiple antennas, single input and single output setups, or multiple inputs and multiple outputs. This angle of arrival estimation aids in spatially separating and classifying individuals in environments with multiple antennas.

In one particular study [72], to find individuals in a given region, an S-band quadrature receiver using coaxial components and doppler radar was used. The main goal of this research was to create an efficient system that could turn off devices when they were not in use, thereby conserving electrical power. This approach not only made the system sustainable but also offered a long-term solution for efficient occupancy monitoring.

13.4.4 Baby Monitoring

Radar-based devices provide an inconspicuous means of monitoring the safety of newborns [73]. These devices can notify carers or parents when a baby rolls over and may be in a position that might impair their breathing. Providing parents with peace of mind lowers the incidence of SIDS (Sudden Infant Death Syndrome) and other sleep-related occurrences.

13.4.5 Movement Analysis with Spectrograms

A spectrogram is a graphic depiction of a signal's fluctuating frequency spectrum. Radar may be used to create spectrophotograms that visually differentiate between the erratic, chaotic pattern of a fall and the steady, walking pattern [74]. This visual aid is crucial for optimising the identification algorithms in environments such as physical rehabilitation programmes or assisted living facilities, where precise movement tracking is necessary. One advantage of using radar for these purposes is that it is less disruptive, can function in any lighting situation, and doesn't require direct physical contact or the subject's active engagement [75]. Because of this, radar is a desirable choice for ongoing surveillance in delicate settings, including hospitals, daycare centres, and senior homes.

13.4.6 Fall Detection

Serious injuries can result from falls, especially among the older population. Radar can identify an unexpected change in altitude and velocity that characterises a fall [76]. By examining the pattern of movement, it can differentiate between routine everyday tasks and a possible fall, and when needed, it may set out warnings for assistance.

13.5 Machine Learning for ADL Monitoring

ML endows a system with the capability to learn from datasets and patterns within the data. In the context of data gathering, various sensors collect data related to distinct ADL characteristics. Consequently, ML algorithms are employed to analyze this data for classifying or detecting ADL, aligning with specific application needs. The most commonly utilized ML algorithms in the field of ADL detection and monitoring include the following.

13.5.1 Artificial Neural Network (ANN)

One kind of ML algorithm that is modeled after the functioning of the human brain is called an artificial neural network, or ANN [77]. Like the brain, which contains billions of neurons that handle information using electrical signals and make choices based on the strength of these signals, an ANN consists of a vast network of linked processing elements. These elements work together to tackle specific issues.

In an ANN, the inputs are represented by variables known as X (such as X0, X1, X2, ..., up to Xn), and each of these inputs is linked to a specific weight, designated as W (like W0, W1, W2, ..., continuing to Wn). These weights signify the importance or strength of each input signal [78].

Additionally, there's a bias function (b) that adjusts the activation function to better fit the network's needs. The activation function is key, as it converts the inputs into the output signal of the ANN. To enhance data classification, the ANN might include several hidden layers between the input and output layers. This structure leads to the ANN being known as a Multi-Layer Perceptron [79]. The output signal from one layer becomes the input for the next layer in systems with hidden layers. For an ANN to react to each input accurately, it must be trained.

The objective of this training procedure is to forecast the result for every input. The difference between the actual and expected values is quantified using a cost function [80]. Each layer's cost function is determined, and the weights are changed for the subsequent input in accordance. Until the cost function is minimized, which denotes a little discrepancy between the actual and anticipated values, this cycle is repeated.

13.5.2 Decision Trees

A group of decision trees make up the random forest method, a kind of supervised classification system. Every decision tree has nodes that represent various tests, and the branches of these trees display the test results [81].

The routes inside the tree are then used to create the categorization. Decision trees, however, are highly sensitive to the training set—even little adjustments to the data can have a big impact on the structure of the tree. The random forest algorithm uses a method known as bagging to combat this [82]. In bagging, several decision trees are created by randomly selecting a sample from the dataset for each tree in the forest [83]. After that, each tree contributes to a class prediction, and the model's most accurate class prediction is chosen by a voting process.

13.5.3 Support Vector Machines (SVM)

The goal of the SVM, a supervised learning model, is to find a hyperplane in an n-dimensional space, where 'n' is the number of features. This hyperplane lowers the n-dimensional space to an (n–1)-dimensional one by effectively splitting the data. While SVM can handle regression, it is mostly used for classification tasks [84].

SVM is divided into two categories: linear and non-linear. To discover the optimal hyperplane that maximizes the separation margin between two classes, the linear SVM assumes [85] that data points are linearly separable. However, the more widely used non-linear SVM first applies a kernel function [86] to alter the input. The model can now locate a discriminant function connected to the hyperplane in the new space as a result of this transformation. Additionally, kernel functions are utilized in various machine-learning algorithms for analyzing patterns.

Data points in SVM are arranged on a plane and can be classified into several groups according to where they are. As a decision boundary, a hyperplane [87] aids in the classification of these data points. Although there are several potential hyperplanes, the main objective is to determine which one maximizes the distance from the closest data points, or support vectors [88]. These support vectors are crucial as they lie close to the hyperplane and significantly influence its positioning.

The SVM seeks to establish a decision boundary at which there is the greatest amount of difference between classes. Because of this feature, SVM is a well liked option for separating different daily living activities from each other.

13.5.4 k-Nearest Neighbors (kNN)

A technique in supervised learning called the k-Nearest Neighbours (kNN) algorithm is used to estimate and categorise different models. It works on the tenet that comparable objects are frequently found close together [89]. In order to compute the Euclidean distance between data points, kNN first determines the number of neighboring points by selecting a value for 'k'. The edges of classes or clusters are defined by this 'k' value. For classification or regression problems, the method selects the top 'k' points from a list arranged by distance. Because of its ease of use and cheap computational cost, kNN is preferred for applications such as recommendation systems and may also help detect behaviors connected to ADLs [90].

13.5.5 Deep Learning

A variety of sensors that can generate significant amounts of data quickly, in enormous quantities, and with great diversity are included in the IoT [91]. ANN with several hidden layers have developed into a deep learning strategy to analyze this large amount of data. Deep learning, distinct from conventional ML algorithms, eliminates the need for separate feature extraction processes. However, training on large datasets can be time-consuming, though the prediction process itself is relatively quick. Like traditional neural networks, the processing in deep learning is often considered a 'black box', making it challenging to fully understand how it operates [92].

13.5.6 k-Means

The k-means algorithm is a widely recognized and straightforward technique in unsupervised ML. It functions by clustering similar data points to uncover patterns [93]. Essentially, it determines the number of clusters (k) in a dataset to classify the data [94]. Each cluster is an aggregation of data points that share characteristics, useful in analyzing specific activities like walking styles or other ADLs. The process involves setting 'k' to define the required centroids in the dataset, with each centroid representing a cluster's central point [95].

Data points are then grouped based on proximity to the nearest cluster, aiming to minimize the size of centroids. This method is commonly employed for clustering analysis and learning distinct features in data. However, the k-means algorithm's performance can be sensitive to minor data variations, potentially leading to significant variances. As a result, its application in ADL monitoring algorithms is somewhat limited.

13.5.7 Linear Discriminant Analysis

Linear Discriminant Analysis (LDA) is a supervised technique often utilized in dimensionality reduction, especially as a preparatory step in data processing [96]. Its primary purpose is to transform high-dimensional data into a more manageable, lower-dimensional form. This transformation is particularly beneficial in reducing both computational cost and resource usage. LDA is notably effective in contexts like gait analysis, where large datasets with similar patterns are collected using wearable devices. Processing this data on low- power devices becomes more viable due to LDA's reduction of data dimensionality. The efficacy of ADL monitoring systems is increased by LDA's capacity to reduce complicated data into basic elements, which helps spot changes in gait patterns that may indicate an ADL-related risk.

13.5.8 Naive Bayes

Known for its simplicity and speed in classification problems, the Naive Bayes algorithm is a kind of supervised learning that is based on Bayes'.

13.5.9 Naive Bayes

Known for its simplicity and speed in classification problems, the Naive Bayes algorithm is a kind of supervised learning that is based on Bayes' Theorem [97]. It generates classes using probability and is effective at producing fast predictions. For instance, it could quickly spot unusual walking patterns in fall detection in ADLs, which aids in the early identification of potential falls. Other strategies, such as decision trees, dynamic time wrapping (DTW), and logistic regression, are also employed in fall prevention in ADLs. Moreover, auto encoders are employed by encoders, coding layers, and decoders in anomaly detection systems for falls [98]. They recognize falls in ADLs by becoming familiar with typical activities and identifying deviations as anomalies, which helps to extract pertinent gait characteristics and minimize the complexity of the data.

13.6 Challenges in RF Sensing

There are several obstacles in the way of RF-based technology, which is becoming more and more popular for monitoring ADL and healthcare, becoming affordable, practical, and efficient. Important difficulties consist of [4].

13.6.1 Durability

One major problem is how well RF-based solutions work in real-world environments. Many times tested in the laboratory, these technologies encounter difficulties in real-world settings. To cut expenses and identify situations like ADLs such as falls immediately, efficient data processing is necessary. Thorough real-world testing is essential to guarantee dependability and prevent false alarms, particularly in critical event detection.

13.6.2 Dependability

While evaluating whether a system is appropriate for a certain situation and while keeping an eye on particular activities, reliability is essential. These technologies need to be user-friendly as well as dependable and fault-tolerant, especially for older users. It is critical to provide senior citizens with training so they can embrace and use this technology appropriately without impairing their functionality. Their regular habits should also be little affected by the solutions. It is anticipated that RF sensing technologies will help the elderly in an emergency, keep an eye on their everyday activities, and monitor vital indications like heart and breathing rates.

13.6.3 Data Privacy and Security

Privacy protection and safe data handling are critical components of healthcare systems, particularly RF-based systems. Even though these devices don't have cameras, their radio frequency data still has to be encrypted and protected. Determining whether the data processing takes place fully at a faraway data center or at the sensor level affects data security needs, thus it is crucial to make this decision.

The radiation from electromagnetic (EM) systems is another issue. Active radar systems need to have their EM emission levels carefully evaluated, even though techniques utilizing currently operational Wi-Fi networks are less risky. Although they often transmit low, non-ionizing frequencies, before they are widely used in monitoring activities of everyday life, the long-term effects of exposure should be taken into account.

13.7 Future Work

Future work in RF sensing to detect different type of daily living activities and ADL should focus on improving signal processing approaches improving signal processing techniques is crucial for enhancing the accuracy and reliability of RF sensing systems. Future research should focus on developing more sophisticated algorithms capable of differentiating between various types daily activities under challenging conditions, such as in cluttered environments or when multiple people are present applying machine learning algorithms to improve detection accuracy, especially in demanding circumstances. The development of comprehensive and dependable monitoring solutions should concentrate on personalizing systems to react to distinct user behaviors and incorporating multimodal sensor data into them. Additionally, to guarantee that these systems are useable by a wide range of users, especially the elderly, accessibility and user-friendliness must be prioritized in their design. To ensure that these systems are user-acceptable and effective, extensive field testing and long-term research are required. It is also critical to manage ethical issues like user permission and data protection.

13.8 Conclusion

This chapter offers a thorough analysis of RF sensing technologies and their use in monitoring ADL. We can produce non-intrusive and extremely accurate monitoring solutions by combining complex ML algorithms with advanced RF sensing techniques, such as radar and Wi-Fi-based devices. Compared to more conventional sensors like accelerometers and cameras, these technologies provide several advantages, particularly concerning privacy and the ability to monitor continuously.

The accuracy as well as reliability of detection systems have been significantly increased by the combination of RF sensing with machine learning techniques like SVM, Random Forests, and deep neural networks. Such advances make it possible to accurately distinguish between distinct ADL and fall scenarios, which improves monitoring systems' overall efficacy.

Even with these developments, several obstacles still exist. Three crucial difficulties that require constant attention include handling the complex details of real-world implementation, addressing the wide spectrum of human behaviors, and ensuring user privacy. The following studies need to concentrate on optimizing algorithms to effectively tackle these obstacles, investigating hybrid systems that include several sensor kinds, and increasing the flexibility of systems to accommodate distinct user settings and actions.

The increasing age of the world's population emphasizes the significance of enhancing ADL monitoring. The integration of advanced RF sensing technology with reliable analytical algorithms offers an achievable path toward the creation of user- friendly, efficient, and successful senior care solutions. These technologies can greatly improve older people's safety and quality of life as long as we keep innovating and addressing current issues.

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Chapter 14
Electrical Impedance Tomography for Non-invasive Screening and Monitoring of Vital Organs

Bradley J. Edelman, Michael Lawson, and Russell W. Chan

Abstract Chronic diseases affecting the lungs, liver, and kidneys contribute to millions of deaths each year and place immense strain on healthcare systems due to their progressive nature and late-stage diagnosis. Existing diagnostic tools such as CT, MRI, elastography, and blood-based biomarkers are effective but costly, inaccessible in remote settings, and are poorly suited for routine community- or home-based screening. Electrical impedance tomography (EIT) offers a highly portable and non-invasive imaging alternative aligned with the goals of Healthcare 5.0. By capturing conductivity-based information in real time, EIT can provide information useful for the early detection of organ dysfunction. The work presented here includes validation studies evaluating the feasibility of EIT for predicting clinical markers associated with lung, liver and kidney function, and for distinguishing healthy versus pathological health states. With the potential for home-based and community-level use, EIT can improve decentralized diagnostics to support early intervention and reduce health burdens in both developed and resource-limited settings.

14.1 Introduction

Healthcare is undergoing a transformative shift towards Healthcare 5.0, where wearable sensing, artificial intelligence (AI), and the Internet of Medical Things play a pivotal role in disease prevention, early diagnosis, and personalized treatment

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[1, 2]. As the incidence of chronic diseases continues to rise globally, the demand for accessible, cost-effective, and scalable diagnostic solutions is more urgent than ever. Among such conditions, chronic obstructive pulmonary disease (COPD), metabolic dysfunction-associated steatotic liver disease (MASLD) (formerly called non-alcoholic fatty liver disease), and chronic kidney disease (CKD) affect a significant fraction of the worldwide population and account for millions of deaths annually either directly or indirectly. Moreover, the progression of these diseases from early dysfunction to life-threatening stages such as respiratory failure, liver cirrhosis, and kidney failure places an enormous burden on healthcare systems. Therefore, timely detection and intervention are critical to prevent irreversible organ damage and to reduce hospitalization rates, healthcare costs, and mortality.

Despite this burden, current gold-standard diagnostic tools such as computed tomography (CT), magnetic resonance imaging (MRI), vibration-controlled transient elastography (VCTE), and blood-based biomarkers are largely inaccessible at the community level due to their cost, requirement for trained specialists, and lack of real-time results. Electrical impedance tomography (EIT), an emerging non-invasive imaging modality with varying levels portability, has gained increasing recognition as an alternative tool for early disease detection, home-based monitoring, and large-scale community screenings [3, 4].

14.1.1 The Global Burden of Chronic Diseases and the Need for Early Detection

The impact of lung, liver, and kidney diseases on public health is staggering. By 2050, COPD is projected to affect over 600 million people globally and is the third leading cause of death, accounting for over 3 million deaths annually [5, 6]. The progressive nature of COPD leads to severe respiratory impairment, frequent hospitalizations, and increased mortality if left untreated. Furthermore, current diagnostic methods such as spirometry are rarely available outside hospital settings, limiting early detection and disease management in underserved communities.

MASLD is the most prevalent chronic liver disease, affecting over 1 billion people worldwide, with a global incidence of 47 per 1,000 people [7, 8]. While MASLD is initially benign, one-third of patients progress to liver fibrosis, cirrhosis, or hepatocellular carcinoma, a leading cause of liver-related mortality. Alarmingly, MASLD is asymptomatic in its early stages, making early detection crucial. Standard diagnostic tools such as MRI-derived proton density fat fraction (MRI-PDFF) and VCTE are highly effective but also extremely costly and impractical for routine community screening.

CKD affects over 850 million people globally and is one of the fastest-growing causes of mortality [9]. In fact, every year over 2 million people worldwide require dialysis or kidney transplants due to CKD progression, and an additional 1 million die due to end-stage renal disease [10]. Patients with undiagnosed CKD also face an increased risk of cardiovascular disease, kidney failure, and premature death. However, CKD is often silent until its late stages, and current diagnostic methods such as creatinine tests, urinary albumin levels, and blood serum-based estimated glomerular filtration rate (eGFR) are minimally invasive, require laboratory operators and delayed processing, and can lead to complications such as bleeding and bruising at the puncture site.

Given these alarming statistics, early detection at the primary healthcare and community level is critical for reducing disease burden, healthcare costs, and mortality rates.

14.1.2 Primary Healthcare and the Role of Community-Based Screening

Primary healthcare serves as the first line of defence in disease prevention and early intervention. However, traditional hospital-centric models struggle to deliver timely diagnostics, particularly in rural or resource-limited settings where access to MRI, CT, and specialized blood tests is restricted.

Community-based screening programs provide an effective solution by identifying at-risk individuals before symptoms manifest, enabling early intervention, and reducing the need for costly hospital treatments. The World Health Organization and numerous governments worldwide have prioritized early disease detection under frameworks such as Healthy China 2030 and universal health coverage initiatives [11, 12]. However, the lack of affordable and portable imaging devices has hindered large-scale implementation.

This is where wearable, portable EIT emerges as a disruptive technology. Unlike CT, MRI, or ultrasound/elastography, which require trained professionals, hospital visits, and expensive machinery, EIT offers a non-invasive, radiation-free, real-time imaging method. EIT is low-cost, portable, and easy to use, making it suitable for home-based, telemedicine, and community-level screening. By enabling early screening for COPD, MASLD, and CKD in community clinics, telemedicine settings, and even at-home monitoring, EIT can empower primary healthcare providers to intervene before irreversible damages occur.

14.1.3 The Role of EIT in Healthcare 5.0

EIT operates by applying micro-currents to the body through a wearable electrode array and measuring voltage changes to reconstruct an internal conductivity map. The variations in conductivity reflect tissue composition and function, allowing for non-invasive health assessment of vital organs such as the lung, liver, and kidney.

Recent EIT systems have achieved encouraging results in assessing lung function, detecting regional airflow limitations, COPD severity, and identifying asthma-related dysfunction [13–15]. In addition, in liver disease screening, EIT has predicted hepatic fat accumulation (MASLD) with moderate sensitivity/specificity and differentiated healthy and diseased liver tissue at greater than chance accuracy [16, 17]. Finally, proof-of-concept work has demonstrated that EIT can be used to distinguish healthy individuals from CKD patients while also predicting eGFR levels with adequate correlation values [18, 19].

14.2 Clinical Validation of EIT for Multiple Organ Function

14.2.1 Description of EIT Studies

To demonstrate the clinical utility of EIT across multiple organ systems, we present here a series of validation studies evaluating the use of this technology for assessing lung, liver, and kidney function. In all cases, both EIT data and ground truth measurements were acquired using gold standard organ system evaluation techniques from the same individuals for comparison and assessment (Fig. 14.1). For lung function, EIT- and spirometry-derived lung function metrics are compared in healthy individuals and patient populations with impaired pulmonary systems. In the hepatic study, EIT-derived features were combined with demographic and anthropometric variables to predict stages of MASLD using both VCTE and MRI-PDFF as references. Finally, we examined the ability of EIT-derived features for predicting eGFR as assessed from in vivo blood serum samples in both healthy individuals and patients suffering from different stages of CKD. These studies include healthy controls and patients at various stages of disease, ensuring robust validation across diverse populations.

14.2.2 Informed Consent

All studies were conducted at Queen Mary Hospital, Hong Kong, and were approved by the Institutional Review Board of the University of Hong Kong, Hospital Authority Hong Kong West Cluster. Written consent was obtained from all participants before study enrolment. A total of 335 individuals participated in the studies presented below.

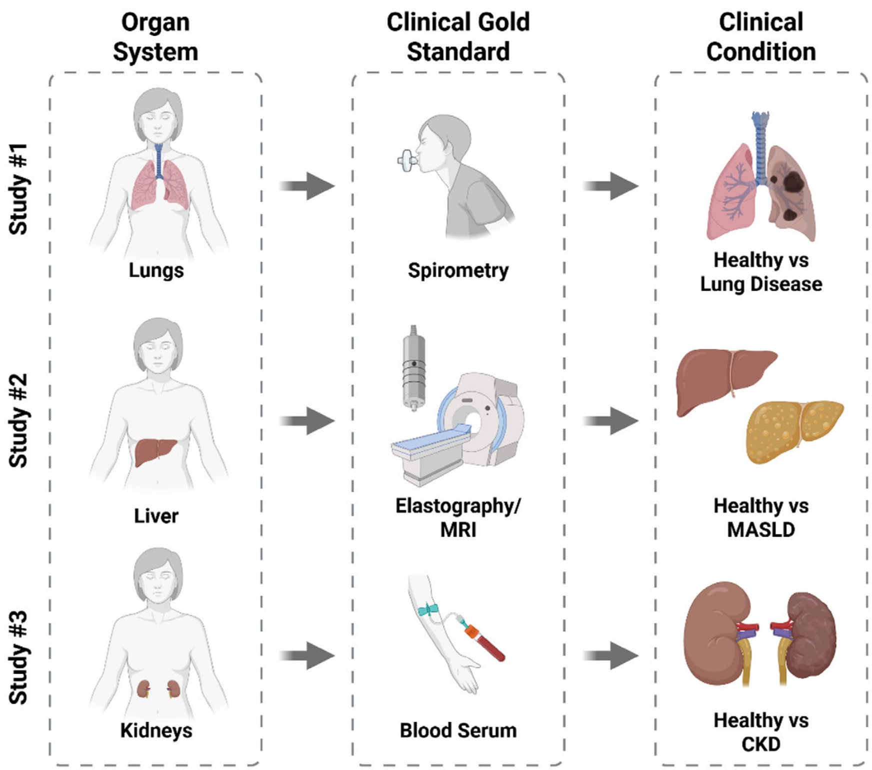

Fig. 14.1 Outline of EIT-based verification studies presented in this chapter. These studies aimed to validate EIT for assessing lung (study #1), liver (study #2) and kidney (study #3) function by comparing EIT-derived features to ground truth measurements acquired by spirometry, vibration-controlled transient elastography/magnetic resonance imaging, and blood serum, respectively. In particular, these studies also investigate the utility of EIT to assess the distinction between healthy individuals and those suffering from various lung diseases, metabolic dysfunction-associated steatotic liver disease (MASLD), or chronic kidney disease (CKD). *Created in BioRender. Edelman, B. (2025)* https://BioRender.com/9yp1iep

14.2.3 Assessment of EIT to Derive Clinical Parameters

In all studies described below, EIT-derived features extracted from cleaned time- or frequency-difference images were compared alongside gold standard clinical counterparts (Fig. 14.2). Regression and classification analyses provide benchmarks to assess the suitability of EIT for identifying clinical markers of various health conditions. EIT data was collected using a 16-electrode portable EIT system (Mediscan, Gense Technologies Ltd., Hong Kong) consisting of an electrode belt, 15.2 × 11.0 × 4.4 cm^3 console, mobile app interface, and cloud-based processing pipeline. The electrode belt was placed circumferentially around the upper or lower abdomen, and electrical measurements were recorded at 33 frames per second a using an adjacent stimulation-measurement pattern. Time-difference EIT utilized a 35kHz stimulation frequency whereas frequency-difference EIT utilized various frequencies between 20 and 300 kHz.

EIT images were reconstructed using a custom pyEIT-based pipeline, utilizing a Gauss–Newton solver with NOSER regularization [20]. Data pre-processing generally involved filtering out noisy signals due to subject movement. Time-series preprocessing also included bad frame rejection and temporal filtering using a moving average approach [13].

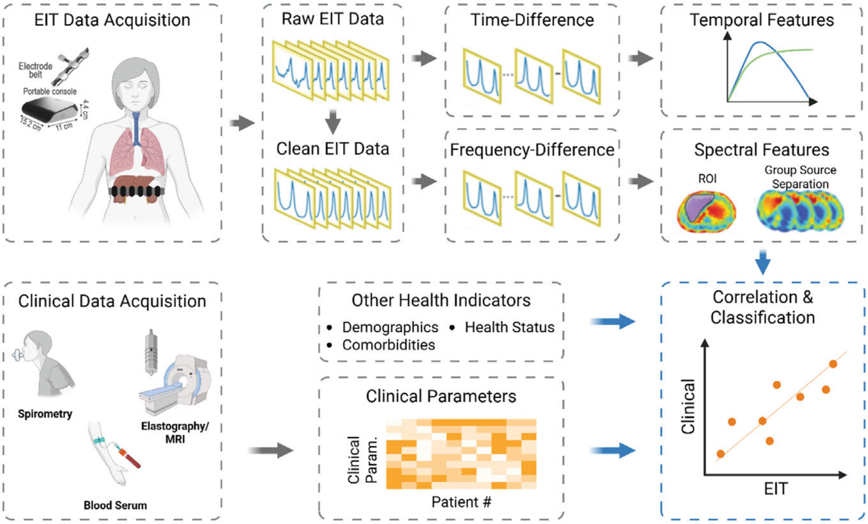

Fig. 14.2 Overview of EIT benchmarking against clinical parameters. After acquiring raw EIT data from a standalone device, it is pre-processed using data filtering and artifact rejection techniques. Data is then post-processed using either a time- or frequency-difference approach, after which EIT-derived temporal or spectral features are extracted. These EIT-derived features are thought to best represent clinical counterparts acquired from gold standard measurements for a disease of interest. After being combined with additional health indications and parameters, correlation analyses are conducted to assess the ability of EIT-derived features to predict clinical parameters. In addition, classification analyses are performed to evaluate if and to what extent EIT-derived features can predict the stratification of disease stage. *Created in BioRender. Edelman, B. (2025)* https://BioRender.com/dva7kii

14.3 Lung Function Assessment Using EIT

14.3.1 Background and Clinical Need

Lung diseases such as COPD, asthma, interstitial lung disease (ILD), and bronchiectasis are among the leading causes of mortality and morbidity worldwide. Standard diagnostic methods include spirometry, chest X-ray, and CT [21, 22]. Spirometry in particular comes packaged in a standalone device and simply relies on subjects performing a series of forced inhales and exhales to determine global lung indicators. Spirometry measures three primary lung function metrics (see Sect. 3.3.1) associated with the speed and volume of air that can be forcefully exhaled [23]. These metrics serve as clinical benchmarks for differentiating healthy individuals from those with impaired respiratory function. Nevertheless, spirometry lacks spatial resolution and is not able to provide regional assessment of lung health. To provide a more comprehensive view of lung function, previous work explored the ability of EIT to predict spatially resolved spirometry indicators from healthy subjects who performed forced breathing at different effort levels to simulate varying degrees of respiratory disease conditions [15]. While this work suggested that EIT could effectively capture different levels of forced breathing, validation on patient populations is necessary to demonstrate clinical value. To expand this work to clinical populations, the current study assesses simultaneous EIT and spirometry parameters in patients suffering from various debilitating lung conditions.

14.3.2 Materials and Methods

Study Participants

A total of 47 patients with various respiratory diseases and 41 health individuals participated in this study. Lung disease patients included those diagnosed with COPD ($n = 8$), asthma ($n = 10$), ILD ($n = 13$), bronchiectasis ($n = 8$), and other lung diseases ($n = 8$) such as left pneumonectomy, lung cancer, lung tumor, lymphangioleiomyomatosis, motor neuron disease, heart failure, myopathy, and bronchiolitis obliterans syndrome. Exclusion criteria included individuals with implanted electronic devices, metal implants, unstable heart/lung conditions, and pregnant women.

EIT and Ground Truth Data Acquisition

All participants underwent simultaneous EIT and spirometry measurements to evaluate the feasibility of EIT in predicting standard lung function indicators. Time-difference EIT data was acquired according to Sect. 2.3. Ground-truth lung spirometry metrics were assessed using a Vmax 22 Encore spirometer (Carefusion GmbH, Germany) according to its standard operating procedure.

14.3.3 Data Analysis

Feature Extraction

Three standard lung function features were extracted from both the EIT and spirometry measurements. For EIT data, forced vital capacity (FVC) was obtained as the difference between the maximum and minimum conductivity changes; forced expiratory volume in one second (FEV_1) was calculated as the difference between the conductivity change at the starting time of the exhalation and one second after, where the starting time is computed using back-extrapolation; and the Tiffeneau-Pinelli indicator (FEV_1/FVC ratio) was computed as the ratio between these two metrics. The same metrics were automatically provided by the spirometer machine via a digital readout.

Regression Analysis for Spirometry Indicator Prediction

Linear regression models were utilized to estimate spirometry indicators from EIT-based features and anthropometrics (i.e. chest circumference, weight, heigh, BMI, and age). The models were evaluated using a 72%/28% training/testing set split.

14.3.4 Results

Performance of Spirometry Indicators Prediction Models

This study demonstrated a notable correlation between EIT-based predictions and ground-truth spirometry values (Fig. 14.3). We observed a Pearson correlation coefficient of $r = 0.78$ ($p < 0.0001$) and $r = 0.73$ ($p < 0.0001$) in the training and testing set, respectively, for the prediction of FVC. Similarly, the Pearson correlation coefficient for FEV1 was $r = 0.77$ ($p < 0.0001$) and $r = 0.70$ ($p < 0.0001$) for the training and testing set, respectively. Finally, the FEV_1/FVC ratio achieved a correlation of $r = 0.61$ ($p < 0.0001$) and $r = 0.55$ ($p < 0.0001$) in the training and testing set, respectively. These findings indicate that EIT has a strong predictive capability for standard spirometry measures.

Distinction Between Healthy and Diseased Individuals

EIT successfully distinguished lung disease patients from healthy controls (Fig. 14.4). COPD patients exhibited significantly lower FEV_1 and FEV_1/FVC ratios, while asthma patients showed reduced FEV_1 and FVC, but normal FEV_1/FVC ratios. Bronchiectasis patients exhibited lower FEV_1 but normal Tiffeneau-Pinelli indicator values, and ILD patients displayed reduced FVC and FEV_1 compared to healthy controls. These distinctions support the potential of EIT in providing diagnostic insights beyond standard spirometry.

Regional Mapping of Lung Function Indicators

EIT's functional spatial maps provide unique insights into regional characteristics of various lung conditions (Fig. 14.5). Compared to healthy controls, patients with lung diseases, except for asthma patients, exhibited notably lower FVC and FEV_1 values across the lung ROIs. COPD patients in particular also revealed notably lower Tiffeneau-Pinelli indicator values through the lung regions. Furthermore, asthma patients appear to exhibit localized airway obstructions on the EIT maps, a feature that is generally not detectable using conventional spirometry. These regional differences highlight the added diagnostic value of EIT in assessing lung function at a more granular level.

14.3.5 Discussion: EIT for Lung Dysfunction

This study demonstrated the feasibility of using EIT as a non-invasive tool for lung function assessment in both healthy individuals and lung disease patients. The results indicate that EIT can predict standard spirometry indicators such as FVC, FEV_1, and the Tiffeneau-Pinelli indicator with high accuracy. Additionally, EIT provides regional lung function mapping, offering further insights beyond the traditional global metrics historically provided with spirometry. In particular, distinct EIT-based patterns of lung function were observed across lung disease groups. In this sense, and as observed in other studies, not only do respiratory conditions induce EIT-based functional maps that are distinct from healthy controls, but also amongst themselves [24, 25]. For example, the regional FEV_1 and Tiffeneau-Pinelli indicator maps were notably different between the conditions of COPD and asthma, and between asthma and bronchiectasis. These distinctions suggest that EIT may be able to provide predictive power for disease classification. Nevertheless, no classification analysis was performed here and therefore, little is known regarding the

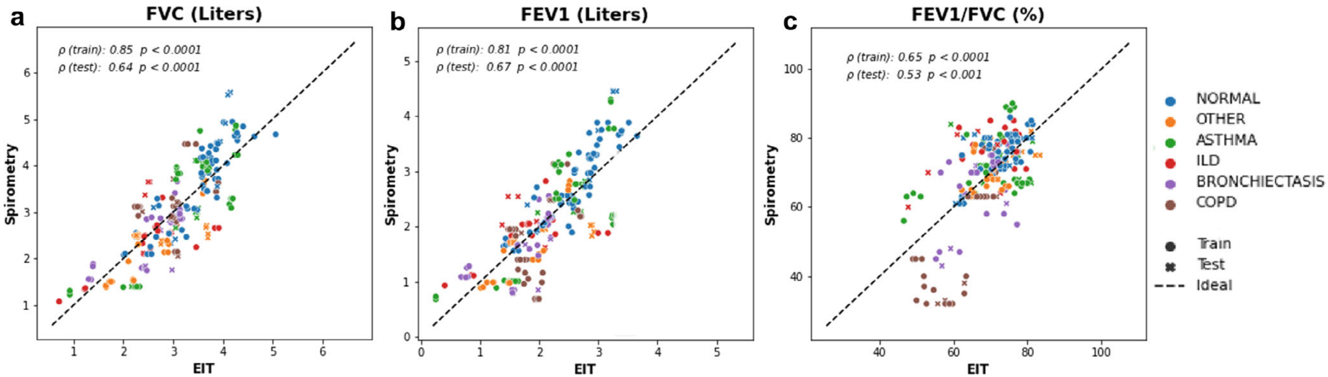

Fig. 14.3 Scatter-plots comparing **a** forced vital capacity (FVC), **b** forced exhale volume in one second (FEV_1), and **c** Tiffeneau-Pinelli indicator (FEV_1/FVC) values derived from EIT and spirometry measurements. Significant correlations were observed between these two measurements for all metrics in both the training and testing sets. Modified from [13] with permission

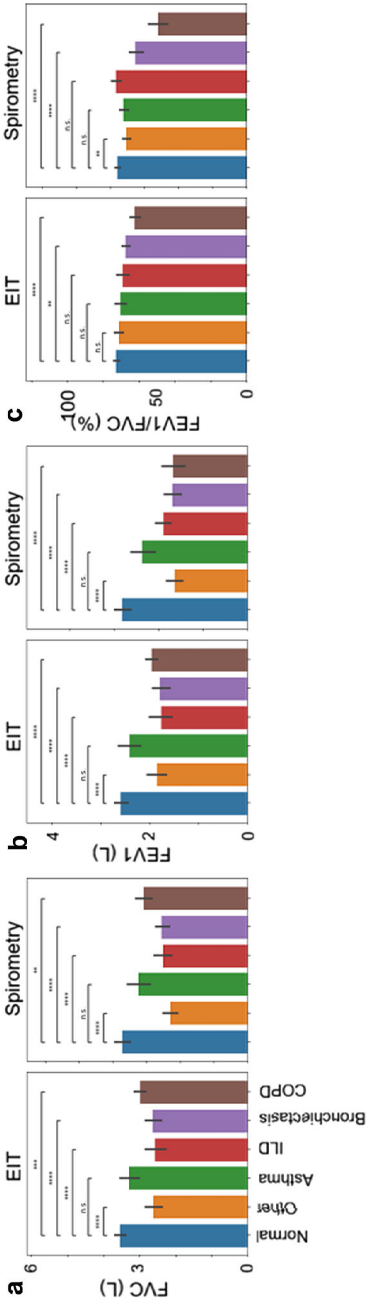

Fig. 14.4 Bar-plots of the global spirometry indicator values for **a** FVC, **b** FEV_1, and **c** Tiffeneau-Pinelli indicator (FEV_1/FVC) across healthy and lung disease patients. Overall, similar group-level values were observed between ET-derived and true spirometry values for all participant groups. In particular, healthy controls exhibited significantly higher FVC and FEV_1 values when compared to ILD, bronchiectasis, and COPD patients. n.s.: not significant, **: $p < 0.01$, ***: $p < 0.001$. Modified from [13] with permission

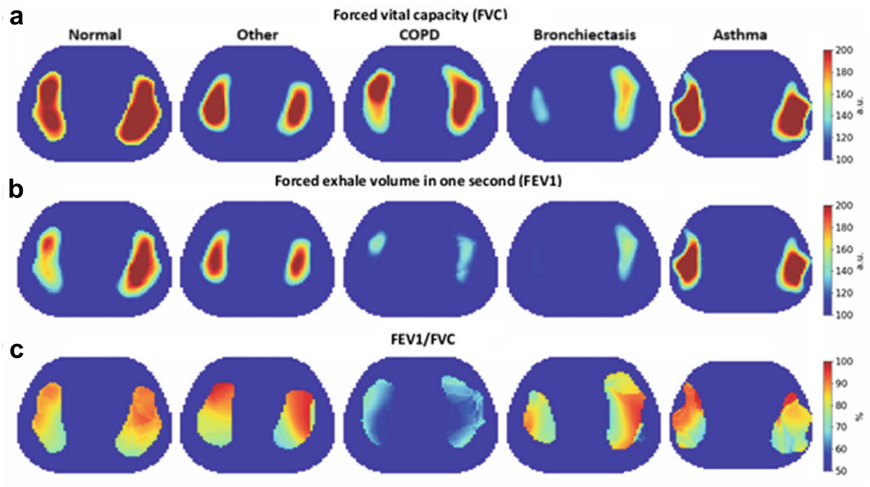

Fig. 14.5 Average regional spirometry indicator maps for **a** forced vital capacity (FVC), **b** forced exhale volume in one second (FEV_1), and **c** the Tiffeneau-Pinelli indicator (FEV_1/FVC). Most notably, compared to healthy controls, COPD patients exhibit noticeably lower regional FEV_1 and FEV_1/FVC values, and bronchiectasis patients lower regional FVC and FEV_1 values. Modified from [13] with permission

sensitivity and specificity of this technique. In addition, while this work presented spatial maps of spirometry indications, this information was not quantified or utilized to differentiate the various participant groups. In fact, identifying regional imaging-based biomarkers for different diseases would likely aid in the diagnostic power of EIT and provide further insight into the mechanisms of such diseases. In addition, expanded clinical trials encompassing a wider range of disease types (e.g. cystic fibrosis, pulmonary hypertension, etc.) [26, 27], disease stages, and comorbidities, are essential to provide the necessary training data to advance these algorithms.

14.4 Liver Disease Screening Using EIT

14.4.1 Background and Clinical Need

MASLD is one of the most prevalent hepatic ailments worldwide and, if left untreated, can lead to severe conditions with alarmingly poor prognoses [28]. Traditional methods for MASLD diagnosis include MRI-derived proton density fat fraction (MRI-PDFF), which quantifies fat content by measuring the relative signal from fat and water protons in liver tissue [29], and VCTE, which measures the controlled attenuation parameter (CAP) that is also proportional to fat content [30]. Even though both of these approaches are accurate, non-invasive and low-risk, complicated and costly operating procedures markedly limit their accessibility for home-based or community screening programs. Fortunately, EIT has demonstrated that tissue conductivity differences in the liver correlate with fat accumulation, offering a non-invasive proxy for hepatic steatosis. These findings have shown translational potential across both controlled ex vivo porcine models and preliminary human studies in overweight individuals, supporting the feasibility of EIT for liver fat quantification and early MASLD screening [31, 32]. To build on these findings, in the current work, the ability of EIT to extract imaging biomarkers correlated with MRI-PDFF and VCTE (i.e. CAP) was examined. These EIT-derived features were also assessed in terms of predicting healthy individuals from those diagnosed with MASLD, as well as their clinical disease stage.

14.4.2 Materials and Methods

Study Participants

A total of 121 subjects participated in the study. These individuals ranged in age from 21 to 84 years old, with a waist circumference between 65 and 127 cm and a body mass index (BMI) value between 18.9 and 43.3. Demographic data, anthropometric measurements, and medical histories were collected before imaging.

EIT and Ground Truth Data Acquisition

All subjects first underwent VCTE-based CAP measurement using a FibroScan machine (Echosens, France) [33], followed by three EIT acquisitions using the frequency-difference method described in Sect. 2.3. Specifically, an injected current at 50 kHz was used as a reference, and difference images were generated using injected currents at 80 kHz and 160 kHz. A subset of 34 subjects also underwent MRI imaging for additional validation. MASLD stage was defined according to the following CAP criteria: Healthy: (CAP $<$ 249 dB/m); Mild: (CAP: 250–269 dB/m); Moderate: (CAP: 270–279 dB/m); Severe: (CAP: >280 dB/m) [34]. Similarly, MASLD stage defined according to the following MRI-PDFF criteria: Healthy (MRI-PDFF: <10%); Not-Healthy (MRI-PDFF: > 10%) [35].

14.4.3 Data Analysis

Feature Extraction

Conductivity difference images at 80 kHz and 160 kHz were selected as predictive features. Additional features were derived by applying group source separation to every pairwise combination of frequency-difference data between 20 and 160 kHz. This process facilitated the isolation of a liver-specific imaging signal. Features were extracted from a liver ROI that was extracted based on prior CT images. VTCE CAP and MRI-PDFF values were extracted according to standard protocols and machine outputs. In addition, clinical self-assessment MASLD scores were acquired from all participants.

Regression and Classification Analysis for CAP and MRI-PDFF

Separate regression models were developed to estimate CAP and MRI-PDFF values from EIT-based features. The CAP prediction model was developed using a linear regression approach incorporating EIT-based features, waist-over-height ratio, weight, height, age, and sex. The MRI-PDFF prediction model consisted of the same architecture and features, in addition to diabetic status, cholesterol levels, and a custom MASLD risk score. Classification was evaluated as sensitivity and specificity using a receiver operating characteristic (ROC) curve analysis. Statistical analysis of MASLD severity classifications was conducted using one-way ANOVA followed by a Bonferroni post-hoc tests to correct for multiple comparisons.

14.4.4 Results

Performance of CAP Prediction and MASLD Stage Classification

EIT-derived and true CAP values exhibited a correlation of $R^2 = 0.29$, with similar significant pairwise differences ($p < 0.001$) between all combinations of MASLD stages (Fig. 14.6a–c). When using a binary classification scheme of health versus not-healthy, EIT-predicted CAP values achieved a sensitivity of 70.9% and a specificity of 73.8%, with an ROC area under the curve (AUC) of 0.76, using EIT-derived values (Fig. 14.6d).

Performance of MRI-PDFF Prediction and MASLD Stage Classification

EIT-derived and true MRI-PDFF exhibited a correlation of $R^2 = 0.22$, and both measurements exhibited significant differences ($p < 0.01$) between healthy and non-healthy NALFD patients (Fig. 14.7a–c). The predicted MRI-PDFF values achieved a sensitivity of 77.8% and a specificity of 80.0%, with an ROC AUC of 0.78, using EIT-derived values (Fig. 14.7d).

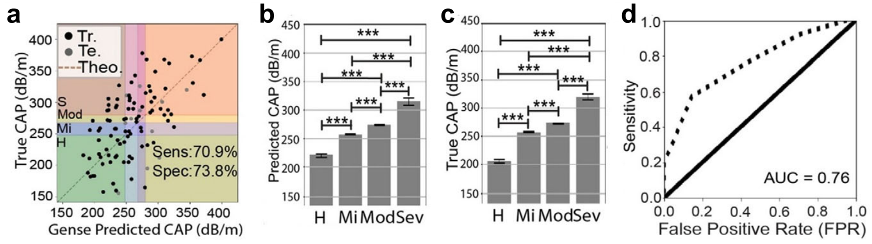

Fig. 14.6 **a** Scatter plot of CAP acquired using EIT versus FibroScan. **(B-C)** Average EIT-derived **b** and FibroScan-derived **c** CAP values for different NAFLD stages. **d** Receiver operating characteristic curve of EIT-derived CAP values for the healthy versus non-healthy (NAFLD) groups. Tr: Training, Te: Testing Theo. Theoretical, H: Healthy, Mi: Mild, Mod: Moderate, Sev: Severe, ***: p < 0.001. Modified from [16] with permission

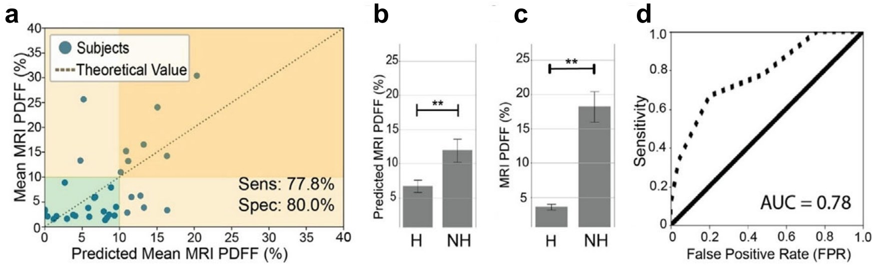

Fig. 14.7 **a** Scatter plot of EIT-derived versus true mean MRI- PDFF. **b**, **c** Average values of EIT-derived **b** and true **c** MRI-PDFF values for healthy and non-healthy (NAFLD) groups. **d** Receiver operating characteristic curve of EIT-derived MRI-PDFF values for the healthy versus non-healthy groups. H: Healthy, NH: Not Healthy, **: p < 0.01. Modified from [16] with permission

14.4.5 MASLD Discussion

This study demonstrated that EIT can be used to predict VCTE CAP and MRI-PDFF values with moderate sensitivity and specificity, demonstrating its potential value as a cost-effective alternative for home- and community-based MASLD screening. For CAP values, group level and pairwise differences between different MASLD stages were similar across the EIT-derived and true measurements. However, the total dynamic range was smaller for the EIT-derived parameters, bringing into question the ability of EIT to classify each individual MASLD disease stage, which we did not explicitly test. We observed a similar effect for the MRI-PDFF results where the distinction between healthy and non-healthy individuals was much more apparent for the true MRI-PDFF values compared to the EIT-derived values (which were still significantly different). With this being said, it is important to note the relatively small MRI sample size (n = 34) used in this study, which constrained model validation and precluded training/testing dataset splitting for MRI-PDFF predictions. The inclusion of non-anthropometric features such as diabetic status and cholesterol levels in the

MRI-PDFF model also raises questions about feature selection. Future work should focus on expanded clinical trials, exploring non-linear modelling techniques, and refining feature selection strategies to improve predictive performance.

14.5 Chronic Kidney Disease Monitoring Using EIT

14.5.1 Background and Clinical Need

CKD includes all renal abnormalities affecting kidney functions and structures which last for more than three months irrespective of clinical diagnosis [36, 37]. While early CKD can be slowed and managed through a variety of treatment protocols, advanced CKD can lead to a debilitating quality-of-life and eventually the need for dialysis. Therefore, early diagnosis and ongoing monitoring of CKD are essential for improving patient outcomes and reducing the long-term health and economic burden on the community. The current standard approach to assess kidney function and evaluate CKD status requires anthropometric information and is prone to bias in early CKD stages. CKD is monitored by obtaining an estimated glomerular filtration rate (eGFR) obtained from the blood serum samples [38]. This approach has shown to be accurate for lower eGFR values, indicating more severe CKD, but is not as reliable for higher eGFR values. Moreover, this approach is mildly invasive and requires lengthy laboratory testing, often on the order of hours to days, to report results. This lack of real-time information creates a gap in the timely assessment of kidney status, particularly in remote and underdeveloped communities. Nevertheless, fibrous tissue similar to that brought on by CKD has been shown to exhibit a dissimilar conductivity profile compared to healthy tissue, which can be detected using EIT [39]. This study investigated the EIT-based signatures of eGFR and the ability of such features to distinguish between healthy individuals and those with CKD.

14.5.2 Materials and Methods

Study Participants

A total of 82 CKD patients and 44 healthy individuals participated in this study. The inclusion criteria encompassed clinically diagnosed CKD patients and healthy volunteers without known renal abnormalities. Exclusion criteria included individuals who had undergone kidney transplantation, recent abdominal surgery, or had implanted electronic medical devices.

EIT and Ground Truth Data Acquisition

Frequency-difference EIT data was acquired as described in Sect. 2.3. Specifically, an injected current at 30 kHz was used as a reference, and difference images were generated using injected currents as 23 other frequencies ranging between 28 and 300 kHz. True eGFR values for each subject were extracted from blood serum samples. Specifically, creatinine level was used to derive eGFR score, as well as the subsequent CKD stages according to the following criteria: Stage 1 CKD: (eGFR > 90 ml/min); Stage 2 CKD: (eGFR: 60–89 ml/min); Stage 3 CKD: (eGFR: 30–59 ml/min); Stage 4 CKD: (eGFR: 15–29 ml/min); Stage 5 CKD: (eGFR: < 15 ml/min) [40]. The CKD stages were also grouped in terms of severity according to the following scheme: normal to mild (Stage 1–2), moderate (Stage 3) severe (Stage 4–5).

14.5.3 Data Analysis

Feature Extraction

General features were derived by applying group source separation to reconstructed images at all contrast frequencies. This process facilitated the isolation of a kidney-specific image signal, and was first only applied to data from healthy individuals as their electrical response is more consistent than patients with various stages of disease. After this, a clear kidney signal emerged at the group level and enabled the extraction of a kidney-source signal and kidney ROI. This ROI was used to extract features from all participants and included the mean conductivity values inside the kidney ROI, outside the kidney ROI, and the ratio between these two values.

Regression and Classification Analysis for eGFR Prediction

A regression model was developed to estimate eGFR using EIT-based features and subject age. The model was trained using a Lasso algorithm, with a five-fold cross-validation scheme and an 85%/15% training/testing set split. CKD stage classification was also performed based on the predicted eGFR values, according the criteria described in Sect. 5.2.2. Classification was evaluated using sensitivity and specificity analyses (i.e. receiver operating characteristic curve). Statistical analysis of CKD severity classifications was conducted using one-way ANOVA followed by a Bonferroni post-hoc tests to correct for multiple comparisons.

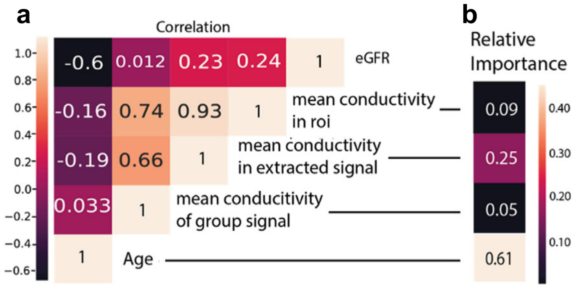

Fig. 14.8 **a** Correlation matrix depicting the pairwise correlation values between true eGFR values derived from blood serum and different EIT-derived features. **b** The relative importance of individual EIT-derived features for predicting true eGFR. Feature importance was determined by fitting a Lasso regression model. Modified from [19] with permission

14.5.4 Results

Performance of the eGFR Prediction Model

In terms of individual pairwise correlations, all EIT-derived features were positively correlated with eGFR values (Fig. 14.8). By contrast, participant age also was negatively correlated with eGFR, consistent with the decline in kidney function with aging. The combined Lasso model with all EIT-derived features exhibited a cross-validated R^2 score of 0.34 for predicting eGFR.

Performance of CKD Stage/Severity Classification

When considering stage 3–5 as "unhealthy" and stage 1–2 as "healthy", the CKD classification scheme achieved a sensitivity of 76.2% and specificity of 74.6%. An ROC curve analysis also yielded an AUC of 0.83, indicating high diagnostic accuracy for CKD classification using EIT (Fig. 14.9a–c). We also used EIT-derived features to predict CKD stage and severity, this time using stage 1–2 as "normal", stage 3 as "moderate" and stage 4–5 as "severe" for the latter categorization. These results demonstrated that EIT-predicted disease stage again worked well for identifying healthy individuals from those moderately ($p < 0.001$) and severely ($p < 0.001$) affected by CKD according to eGFR value (Fig. 14.9d). However, such features performed less well when applied to the finer stratification of five CKD disease stages.

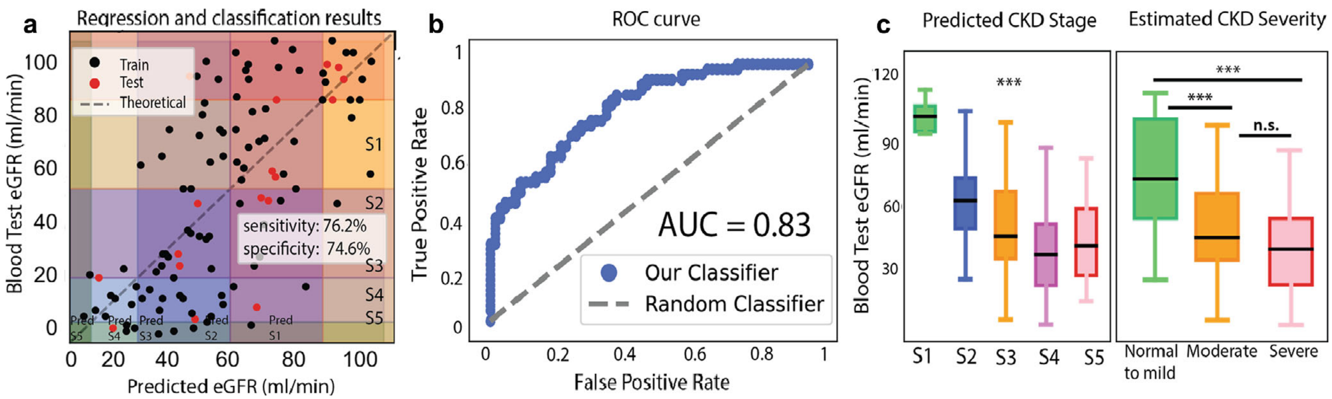

Fig. 14.9 **a** Scatter plot of EIT- versus blood serum-derived eGFR values. **b** Receiver operating characteristic curve of EIT-derived eGFR values for the healthy versus non-healthy groups. **c** Comparison of true eGFR values across CKD stages (1–5) and CKD severity ratings (Normal: stage 1–2; Moderate: stage 3; Severe: stage 4–5) defined by EIT-predicted values. S1: stage 1, S2: stage 2, S3: stage 3, S4: stage 4, S5: stage 5, n.s.: not significant, ***: $p < 0.001$. Modified from [19] with permission

14.5.5 CKD Discussion

This study demonstrated that EIT can potentially serve as a non-invasive and real-time alternative for CKD screening and monitoring. EIT-derived features exhibited a strong correlation with blood serum eGFR values and enabled above-chance classification results between healthy individuals and those with CKD. The role of EIT and clinical metadata could be further clarified with larger clinical trial sizes consisting of a more diverse cohort of participants that encompasses a wider range of ages, ethnicities, and comorbidities. Including even more physiological parameters implicated in CKD, such as blood pressure and hydration status, could also contribute to model refinement [41, 42]. Future studies should also explore the potential of longitudinal EIT monitoring of CKD to assess disease progression and treatment responses. By tracking changes in EIT-derived parameters over time, clinicians could identify distinct spatial and/or spectral biomarkers of CKD. Furthermore, retrospective analyses could lead to a more stratified prediction of CKD before permanent damage occurs. This personalized approach to CKD management could lead to improved patient outcomes and reduced healthcare costs.

14.6 Conclusion

These studies collectively demonstrate the feasibility of using portable, non-invasive EIT systems for assessing lung, liver, and kidney function. Across organ systems, EIT-based models demonstrated strong correlations with gold-standard clinical measures. For lung function, EIT predicted spirometry indicators with a correlation of $r = 0.73$ for FVC and $r = 0.70$ for FEV_1, and successfully differentiated multiple chronic respiratory conditions using regional EIT-based metrics. In our liver study, EIT achieved a classification AUC of 0.76 and 0.78 when predicting healthy versus non-healthy CAP and MRI-PDFF scores, respectively, outperforming basic self-assessment tools and supporting the use of EIT in non-invasive MASLD screening. For kidney function, EIT-derived features predicted eGFR with an $R^2 = 0.34$ and separated healthy individuals from those with CKD with an AUC of 0.83. In all cases, EIT provided real-time insights into regional organ physiology with clear diagnostic accuracy, offering a cost-effective and radiation-free alternative to conventional imaging and laboratory methods. The potential of integrating EIT into home-based and telemedicine platforms supports broader access to early disease detection, personalized monitoring, and timely intervention across multiple organ systems. Continued validation of EIT with larger clinical studies will further solidify the role of EIT in the future of decentralized, preventive healthcare.

14.7 Challenges and Future Directions

While EIT holds promise for non-invasive screening and monitoring of vital organs, several challenges must be addressed to facilitate its widespread clinical adoption. One significant limitation is the low spatial resolution of EIT compared to traditional imaging modalities like CT and MRI. In general, reconstructed EIT images exhibit a spatial resolution of only 2–3 cm [43], which cannot pinpoint small lesions or subtle anatomical changes when compared to the sub-millimeter resolution of CT and MRI. EIT is unlikely to ever achieve a spatial resolution similar to such modalities, however, this technology is notably cheaper, more portable, and easier to use. These key features are encouraging for home-based or remote health screening protocols that would otherwise be incredibly difficult to achieve with traditional imaging modalities. In addition, EIT is continuously evolving, and the integration of higher-density/volumetric electrode arrays, machine learning (ML)-based image enhancement, and sophisticated inverse solutions will be crucial to further improving the reliability of this technology for clinical applications [44–46].

One key challenge of EIT lies in the standardization of data acquisition and analysis protocols, as well as the interpretation of results [47]. Variations in electrode placement, contact impedance, and data processing methods can significantly impact the accuracy and reproducibility of EIT measurements. Establishing standard protocols for data acquisition, quality control, feature extraction, etc. is essential to ensure consistent and reproducible results across different clinical settings and patient populations. This also involves developing robust calibration procedures and creating comprehensive databases of EIT data from diverse patient cohorts, which can serve as reference standards for clinical interpretation and algorithm training. Furthermore, user-friendly interfaces and automated analysis tools are needed to simplify the use of EIT for healthcare professionals who may not have specialised expertise in electrical engineering or signal processing.

This is particularly important when considering the diversity in commercially available EIT devices. There are numerous devices currently on the market, many of which have already received regulatory approval (Class II) in Europe, the USA or China. Some notable examples of these are the PulmoVista 500 from Dräger, ENLIGHT from Timpel Medical, and the Infivision EIT series. These devices are offer onboard, real-time data analysis and display, but are generally built into a cart and intended for hospital settings. In the studies described here, we utilized another portable device developed by Gense (Mediscan), containing an acquisition module and separate tablet display. While this device is tailored to remote- and home-based monitoring applications, it is not medical grade, has received no regulatory approval, and requires many inputs for successful operation, all of which significantly limit usability for non-expert users in healthcare settings. This device also lacks a reference electrode, which can lead to noisy data and, in turn, less reliable and inconsistent diagnostic results [48]. Furthermore, the Mediscan device contains a mandatory built-in patient management system that depends on cloud services. The reliance on mandatory cloud services for patient data management raises significant concerns regarding privacy and security, particularly in light of evolving HIPPA regulations and the FDA's (also the NMDA and EMA) dynamic and cautious stance on cloud-based analysis and AI/ML integration in medical devices [49].

While these drawbacks limit the future integration of the Mediscan device into routine operation, other devices currently under development aim to fix these issues and lower the barrier to healthcare integration. In particular, E-SENSE is developing a similar portable EIT device with a reference electrode strategically positioned far from the primary measurement site. This addition offers the potential to enhance signal stability and mitigate the influence of extraneous factors. To further enhance user experience and regulatory compliance, particularly in resource-constrained environments, this device integrates a compact display directly onto the EIT device and provides an immediate readout of results. All processing of patients' data to produce measurements on organ health take place on device, so data security issues from cloud processing do not arise. This eliminates the reliance on external monitors or computing devices and enables this device to be used as a purely standalone device.

Integrating exemplary commercial EIT devices into clinical practice, whether it be in primary care or remote monitoring, will benefit from the addition of other physiological measurements and clinical data. In the work presented here, we incorporated numerous health indicators into our predictive regression models, including demographic information, health status and comorbidities. As the addition of this information improved the predictive value of the regression model, it is likely that incorporating data from other wearable sensors, physiological measurements and electronic health records could provide a more holistic assessment of patient health and enable more personalised treatment strategies. For instance, integrating blood oxygen saturation levels or metabolic markers could offer a more comprehensive understanding and risk stratification of respiratory impairment or MASLD, respectively. Multi-scale perspectives like this offer not only localized insights into the organ of interest, but also broader information about systemic function, as these markers reflect global physiological status. Similarly, simultaneous ECG and blood pressure measurements could enhance the monitoring and management of cardiovascular conditions and cerebral stroke [50, 51]. The use of EIT for these conditions is modest, however, multi-modal approaches facilitated by advancements in data fusion and ML have the potential to transform EIT from a standalone imaging modality into a powerful tool for comprehensive physiological monitoring.

Beyond these overarching considerations, several practical enhancements could significantly improve the usability and applicability of EIT, particularly in community-based and remote healthcare settings. The development of improved electrodes, such as reusable and/or dry electrodes could markedly improve data quality and ease of use [52]. More specifically, if such electrodes can maintain skin contact while minimizing impedance variability, it would not only streamline the measurement process but also enhance patient comfort and reduce the likelihood of signal artefacts. Additionally, the application of non-linear ML models, such as artificial neural networks or support vector machines, could enhance the accuracy of EIT-based predictions. Specifically, these models are better equipped to capture the complex, non-linear relationships that may be present between tissue impedance and other physiological factors that influence organ system health. However, the successful implementation of such models requires larger and more diverse datasets than those currently available [53, 54], and would likely demand engagement from the EIT community to build open-source repositories.

Finally, large-scale, multi-center clinical trials are crucial to validate the clinical utility and cost-effectiveness of EIT in real-world settings. While the studies presented in this chapter demonstrate the feasibility and potential of EIT for lung, liver, and kidney assessment, larger studies with diverse patient populations are needed to confirm its diagnostic accuracy, sensitivity, and specificity compared to gold-standard methods. These trials should also evaluate the impact of EIT-based screening and monitoring on patient outcomes, healthcare utilization, and overall cost of care. Demonstrating clear clinical benefits and economic advantages will be essential for driving the adoption of EIT by healthcare providers, regulatory agencies, and insurance companies, ultimately paving the way for its integration into routine clinical practice and contributing to the realization of Healthcare 5.0.

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