Received: 20 March 2026 | Revised: 22 May 2026 | Accepted: 1 July 2026 | Published online: 16 July 2026

REVIEW

Smart Wearable Technology
2026, Vol. 00(00) 1–22
DOI: 10.47852/bonviewSWT62029713

BON VIEW PUBLISHING

Multimodal Sensing and Artificial Intelligence–Driven Data Fusion in Wearable Health Technologies, Advances, System Challenges, and Research Frontiers

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Abstract: Multimodal sensing and data fusion using artificial intelligence have transformed wearable health technologies by integrating various physiological signals for continuous health monitoring. This study provides a comprehensive perspective on wearable technologies, such as fusion hierarchies, machine learning interpretation, and deployment in wearable body area networks. The research offers a performance assessment and structural issues affecting reliability, including sensor diversity, dominance, noise, and intermittent data loss due to motion artifacts and dropouts. As a result, it explores multimodal fusion failure modes, demonstrating how asynchronous failure and partial observability can cause instability in multimodal representations. The study also highlights the transition from continuous to event- and window-based processing to improve energy, computational, and clinical efficiency in edge computing. The study explores emerging approaches like self-supervised learning, multimodal foundation models, and digital twin-based personalized health models for enhancing robustness and generalization. The research also considers advances in functional materials, such as mechanochromic materials and biointegrated sensing platforms, to enable intuitive and seamless physiological monitoring. Finally, the work considers the regulatory, energy, and system constraints on these innovations and notes that future wearable systems must combine computational intelligence with physical form factors, interpretability, and safety, with robustness and adaptability being the guiding design principles.

Keywords: AI-driven data fusion, multimodal sensing, wearable health systems, physiological signal processing, edge intelligence

1. Introduction

Wearable health technologies have progressed from basic activity trackers to smart and networked devices that can perform real-time health monitoring and analysis. First-generation wearables were largely unimodal, using the modalities of accelerometers to sense activity or photoplethysmography (PPG) to sense heart rate. These devices were marketable and were used, but their clinical value was limited due to low awareness of context, low physiological coverage, and poor diagnostic accuracy [1, 2]. The advances in flexible electronics, miniaturized sensors, wireless body area networks (WBANs), and embedded artificial intelligence (AI) have transformed wearable systems into multimodal environments. Today's wearables include a variety of physiological and environmental sensing modalities, such as electrocardiography (ECG), electromyography (EMG), electroencephalography (EEG), inertial measurement units (IMUs), temperature sensors, and biochemical sensors. Multimodal integration improves physiological interpretability, noise, and artifact immunity and enables to assess the health status in a holistic way [3–7]. However, this multimodal growth introduces a great deal of complexity due to the variable sampling frequencies, signal dynamics, noise characteristics, and context-dependent variability of physiological signals. Multimodal wearable data are high-dimensional, asynchronous, and noisy and cannot be processed using conventional signal processing techniques.

The evolution of wearable health technologies has proceeded in a systematic fashion from simple, unimodal systems to intelligent, complex, and connected systems. The initial wearable systems, which emerged around 2005, were primarily unimodal, using simple sensors (such as pedometers) to measure limited physiological or activity data, with little clinical value [8, 9]. Around 2010, the integration of sensor technologies led to the development of multimodal systems that captured complementary

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physiological data, such as ECG and motion, thus increasing the contextual understanding and diagnostic capabilities of the system [10, 11]. This journey has led to 2015, where the integration of mobile computing and wireless communication technologies has enabled continuous and real-time health monitoring via interconnected wearable networks [12, 13]. More recently, this evolution has led to the integration of AI, multimodal data fusion, and cloud-based analytics, facilitating scalable, adaptive, and personalized healthcare [14]. This evolutionary process demonstrates the transition from device-centric sensing to system-level smart healthcare systems that can support data-driven and predictive decision-making.

Figure 1 illustrates the technological progression of wearable health systems from simple unimodal sensing platforms toward intelligent multimodal physiological ecosystems. It highlights the transition from rule-based monitoring to AI-driven analytics, edge-cloud intelligence, self-supervised learning (SSL), foundation models, and digital twin architectures. The figure further demonstrates how sensing modalities, computational paradigms, deployment strategies, and system limitations evolved simultaneously, reflecting increasing clinical relevance, contextual awareness, and adaptive physiological intelligence [1, 7, 8, 10, 14, 15].

The diagram in Figure 2 illustrates the collection and preprocessing of multiple physiological signals. It illustrates various biosignals like ECG, PPG, EMG, and motion sensors, along with preprocessing operations such as filtering, normalization, and segmentation. The figure highlights the processes of denoising and synchronization, making the signals from different sensors compatible. It gives insight into how unstructured and noisy inputs are converted to usable signals that facilitate reliable feature extraction and subsequent machine learning (ML) processing [6, 8, 11, 12, 14].

As such, ML and AI algorithms have been the focus of enabling effective feature extraction, data fusion, pattern recognition, and prediction in wearable health systems [16–19]. Data fusion here can be described as the combination of data from different sensor modalities into one clinically relevant representation. Data-level, feature-level, and decision-level fusion strategies are the most common types of fusion, which have trade-offs in terms of computational cost, interpretability, delay, and feasibility of implementation in resource-limited wearable devices [20, 21]. When used successfully, AI-based multimodal fusion has resulted in improved diagnostic performance, reduced false alarms, and personalization in health monitoring. Besides the advancement of algorithms, the advancement of wearable health technologies is also driven by the global healthcare market, such as the increasing aging population, chronic diseases, and healthcare costs. This has led to a greater shift in the healthcare paradigm toward continuous, remote, and preventive care, in which smart wearable systems play an important role in the development of personalized and predictive medicine [22, 23]. Despite these trends, the literature on wearable health is still very fragmented across different disciplines, including sensor engineering, signal processing, ML, and clinical use cases. The existing literature and even recent systematic reviews are more likely to focus on individual parts of the ecosystem, for example, sensing technologies, AI-fusion algorithms, or specific clinical applications, rather than as an integrated system (end-to-end deployable). As a result, it has

Figure 1
Evolution of multimodal wearable AI systems from 2011 to 2026

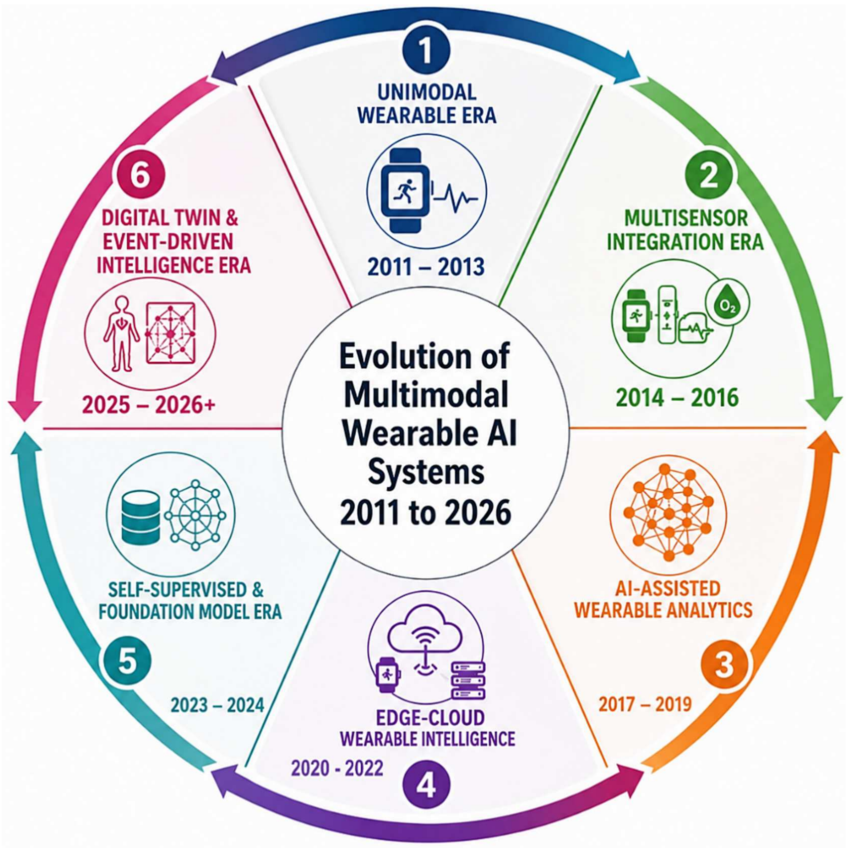
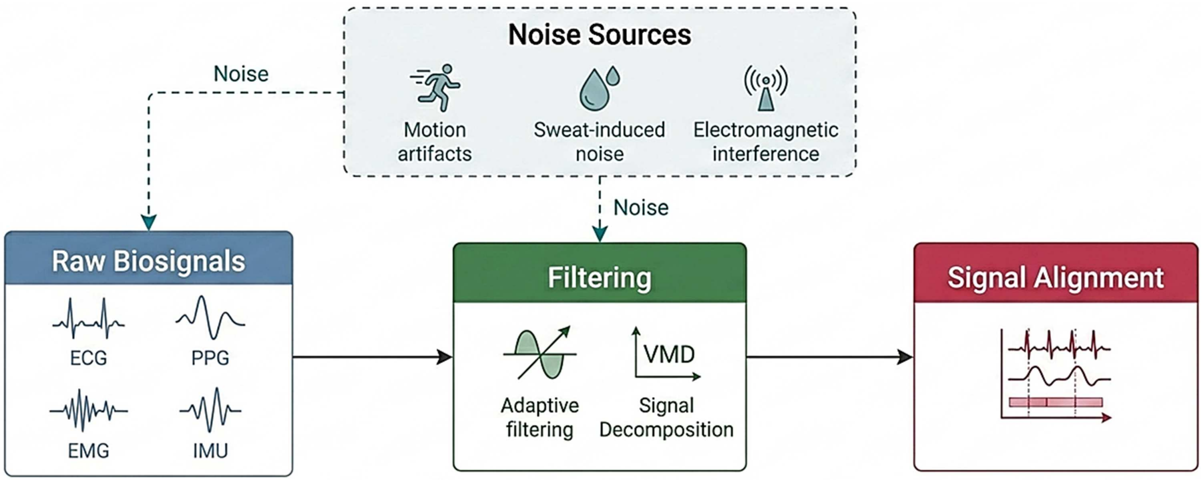


Figure 2
Multimodal signal acquisition and preprocessing pipeline



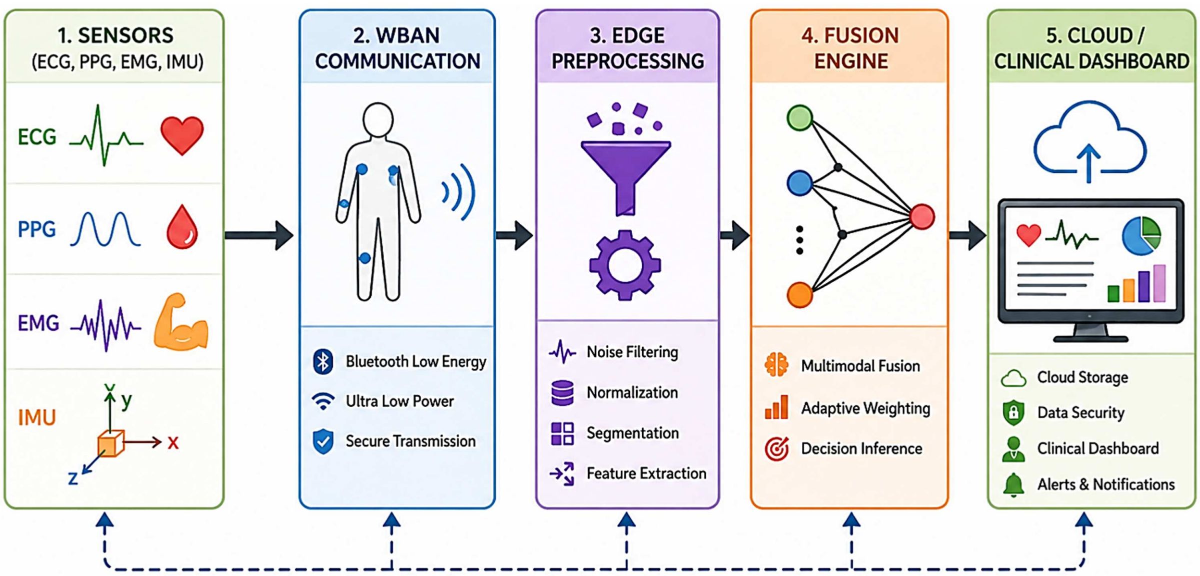
created a gap in the integration that can merge multimodal sensing technologies, AI-based multimodal fusion algorithms, the issues of embedded systems, and clinical translation challenges into a unified analytical system.

Figure 3 shows an overview of a multimodal wearable health monitoring system. It shows the way physiological signals are sensed using body sensors, analyzed at the edge device, and communicated via wireless networks to the cloud. It illustrates the sensing to analysis to clinical interpretation process. It also takes into account system limitations, such as energy efficiency and reliability, and illustrates how various layers work together to provide continuous, scalable, and clinically relevant health information [5, 11, 12, 18, 21].

Unlike the recent review articles that tend to focus on a particular aspect of the field, for example, multimodal sensing platforms [2], wearable AI models [4], or data fusion strategies, this paper presents a unified view of multimodal wearable health systems. Specifically, it brings together sensing, data fusion plans that are based on AI, edge-cloud deployment constraints, and clinical translation challenges in a single framework. In addition, this review complements the current literature that is focused on algorithmic and sensor levels by critically examining the deployment constraints in the real world such as energy, interoperability, privacy, and regulatory compliance. It provides a translational perspective by linking the technical design possibilities with the clinical implementation challenges to close the gap between the current prototype systems and clinically viable multimodal wearable AI systems.

The review addresses the lack of integration of the current literature by providing a comprehensive review of multimodal wearable health systems. It critically examines the integration of sensors, physiological data acquisition, and diverse biomedical data and presents AI-based fusion approaches. Rather than building algorithms, this review compares traditional ML, deep learning, adaptive fusion, and explainable AI to wearable challenges, such as energy efficiency, sensitivity to latency,

Figure 3
End-to-end architecture of multimodal wearable health monitoring system



computational capability, and privacy. In addition, this review considers the system-level issues of deployment, such as edge-cloud computing, embedded intelligence, and secure wireless communication technologies that are deployed to enable continuous health monitoring. Cardiovascular monitoring, neurological assessment, human activity recognition, and chronic disease management are discussed as the primary application domains to identify the current performance trends, the lack of clinical validation, and the deployment challenges.

This review provides a unified approach to understand multimodal wearable health systems, with a consideration of innovations in sensing, AI techniques, and system design. It also identifies the main research gaps and opportunities that can be exploited to ease the development of scalable, robust, explainable, and clinically deployable AI-based wearable health systems.

2. Research Methodology

The research follows a systematic literature review methodology based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines. This guarantees clarity, replicability, and rigor in the identification, screening, and synthesis of existing literature on multimodal sensing and AI-based data fusion for wearable health technologies. The approach aims to reflect the multidisciplinary nature of the topic, with interests in biomedical engineering, signal processing, ML, embedded systems, and clinical health informatics.

2.1. Data identification and search strategy

A literature review was conducted in major scientific databases, such as *IEEE Xplore, PubMed, ScienceDirect* (*Elsevier*), and *MDPI*. These were selected for their breadth of coverage of biomedical engineering, AI, wearables, and health analytics journals. The study considered papers published from 2011 to 2025, the period during which multimodal wearable sensors, WBANs, and AI-based health analytics systems emerged. Some earlier seminal papers were also included where necessary to contextualize theory and architecture.

Expanded Multi-Domain Keyword Strategy

To minimize selection bias and ensure broad coverage, a multi-cluster keyword strategy was developed. The search strategy was tailored to the multidisciplinary nature of wearable health systems:

1) Wearable sensing and physiological monitoring

"wearable biosensors," "physiological monitoring wearable," "ECG wearable," "photoplethysmography OR PPG," "electromyography wearable," "electroencephalography wearable," "inertial measurement unit OR IMU"

2) Multimodal fusion and artificial intelligence

"multimodal data fusion," "sensor fusion healthcare," "deep learning biosignal analysis," "transformer physiological signals," "time series classification wearable," "self-supervised learning biosignals"

3) System architecture and embedded intelligence

"wireless body area network OR WBAN," "edge computing healthcare," "TinyML wearable systems," "federated learning healthcare," "low power embedded AI"

4) Clinical applications and digital health systems

"remote patient monitoring," "arrhythmia detection wearable," "chronic disease monitoring wearable," "digital health systems," "physiological signal analysis healthcare"

Boolean Query Construction

Search queries were structured using Boolean operators to improve precision and coverage, for example:

(("wearable" OR "body sensor network" OR WBAN) AND ("multimodal" OR "sensor fusion" OR "data fusion") AND ("machine learning" OR "deep learning" OR "artificial intelligence") AND ("health monitoring" OR "physiological signals"))

Search Enhancement Strategy

To improve completeness, backward and forward citation tracking (snowballing) was applied to key papers. This ensured inclusion of influential studies that may not have been captured in database keyword searches alone.

Initial Retrieval

The search strategy yielded 1,345 records. This reflects broad interdisciplinary coverage across multiple databases and keyword clusters rather than limited search sensitivity.

2.2. Eligibility criteria

A structured inclusion and exclusion framework was applied to ensure relevance, methodological quality, and alignment with multimodal wearable system objectives.

Inclusion Criteria

Studies were included if they met the following conditions:

1) Focused on wearable or body-mounted physiological monitoring systems
2) Incorporated multimodal sensing or multi-sensor data fusion
3) Applied ML or AI techniques
4) Provided sufficient methodological detail for analysis or replication
5) Were peer-reviewed journal articles or conference proceedings
6) Published in English between 2011 and 2025

Exclusion Criteria

Studies were excluded if they:

1) Focused on unimodal sensing without fusion strategies
2) Lacked sufficient methodological description
3) Were editorial, commentary, or opinion-based works
4) Were purely simulation-based without wearable system relevance
5) Were duplicate records across databases

Rationale for Selection Strictness

While a wide search was conducted, stringent inclusion criteria were applied to include only studies that contributed to end-to-end multimodal wearable health systems. This was to ensure consistency in sensing, fusion, AI, and system-level deployment. This accounts for the drop from 1,345 to 52 studies. This is due to methodological focus and stringent filtering, not search scope. Wearable and ambient sensing systems were excluded during the initial screening to preserve the focus on the methodology but are recognized as extensions in the discussion of system-level integration.

2.3. Study selection process

The study selection process was based on the PRISMA 2020 guidelines. Duplicates were removed, and titles and abstracts were reviewed. Full-text screening was then performed to determine whether the methods were in line with the inclusion criteria. Screening was conducted independently, with any disagreements resolved through discussion to minimize bias. We found 1345 records. We excluded 225 duplicates, leaving 1120 records to screen. 732 were removed due to being unrelated to multimodal wearable systems. The remaining 388 full-text articles were screened, with 336 excluded for either methodological issues or non-peer-reviewed status. A total of 52 studies were synthesized.

Figure 4 provides an overview of the study selection process. It shows the steps taken, from the initial search to the removal of duplicates, to the screening of titles and abstracts, to the assessment for eligibility of the full text, and finally to the inclusion of the studies. This diagram shows the flow of studies, with the number decreasing at each stage, allowing for transparency and rigor. It allows the reader to see how the final list of reviewed articles was arrived at and demonstrates compliance with systematic review guidelines.

2.4. Quality assessment of included studies

Included studies were evaluated using qualitative methodological criteria, including:

1) Clarity of experimental design and methodology
2) Dataset size, diversity, and acquisition duration
3) Validation strategy (cross-validation, external validation, or clinical validation)
4) Transparency of performance metrics
5) Applicability to real-world multimodal wearable systems

Studies that were poorly reported or had limited reproducibility were interpreted critically or given less weight in the analysis.

2.5. Data extraction and synthesis

Relevant data were systematically extracted from each study, including:

1) Sensor modalities used
2) Fusion strategy (data, feature, or decision level)
3) AI or ML model type
4) Dataset size and duration
5) Application domain (clinical or functional)
6) Performance metrics and validation methods

Data were synthesized using thematic and comparative analysis. This allowed us to identify trends in multimodal integration approaches, AI model development, and system-level deployment issues.

2.6. Protocol registration and reporting considerations

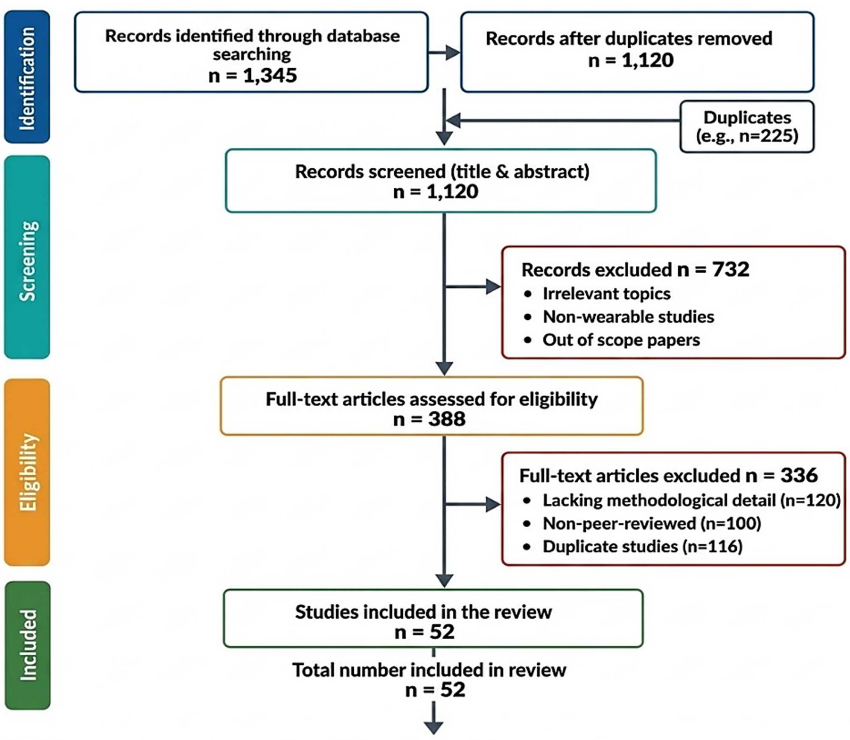
The review was not registered in an international database such as PROSPERO due to its engineering systems focus. However, reporting was fully aligned with PRISMA 2020 guidelines to ensure transparency and reproducibility.

The methodology prioritizes systems-level integration rather than meta-analytic statistical aggregation, reflecting the interdisciplinary nature of wearable health technologies.

3. Physiological Signal Modalities and Multimodal Interaction Dynamics

Multimodal wearable health systems combine diverse biosignals like electrocardiogram (ECG), photoplethysmogram (PPG), electromyogram (EMG), electroencephalogram (EEG),

Figure 4
Flow diagram of the study selection process



accelerometer data, and biochemical markers for holistic monitoring. These modalities are not a set of independent data but a tightly integrated sensing system whose performance depends on the nature of interaction, degree of synchronization, and robustness against noise and environmental variability [1, 2, 20, 24].

In practice, each sensing modality not only provides different trend monitoring of physiological information but also introduces unique vulnerabilities. ECG provides high resolution of the electrical activity of the heart but is highly sensitive to placement, motion artifacts, and impedance variations [20, 25]. PPG, widely used in wearable devices, is vulnerable to peripheral blood flow, motion artifacts, and skin scattering changes, thus limiting its effectiveness in free-living monitoring [1, 26]. EMG introduces high-frequency information of muscle activity, which is strongly correlated to motion artifacts, especially in rehabilitation and motion recognition [6, 27, 28]. EEG adds neurological information to the system but has a low signal-to-noise ratio and may be contaminated by environmental artifacts.

A system-level challenge is multimodal artifacts, when artifacts of one sensor affect feature representations of other sensors. For example, motion artifacts occur in both PPG and accelerometers and induce similar artifacts that can be mistakenly interpreted by a fusion model as physiological interactions. This breaks the assumption of conditional independence of many standard fusion approaches [19, 28]. Asynchrony and misalignment also need to be considered. Wearable sensors have different sampling rates and can be located in different areas of the body (e.g., chest, arms, legs), which means data are not collected simultaneously. This has a bearing on the sequence models including long short-term memory (LSTM) and transformers, whereby it introduces artificially correlated phase relationships [29, 30]. Additionally, sensor inconsistencies and drift affect fusion stability. Variations in device design, sensor placement, and wear lead to biases across sensors, particularly optical and bioelectrical sensors [1, 31]. Without continuous adaptation and calibration, these biases compound and skew multimodal feature spaces and affect the generalization of system performance across devices and subjects.

Collectively, multimodal interactions in wearable systems are not only linear integration problems but also nonlinear coupling problems that are dictated by interference, desynchronization, and competition between different modalities. These processes constrain the effective performance of the system in real-world health monitoring.

4. Fusion Architectures and Real-World Failure-State Analysis in Wearable Artificial Intelligence Systems

Multimodal integration approaches in wearable health systems are commonly classified into three levels of fusion: data level, feature level, and decision level.

Figure 5 illustrates the integration of data from different sensors at various levels of fusion. It illustrates asynchronous signal inputs to feature extraction blocks, followed by organized fusion at the data level, feature level, and decision level. It shows the flow of information through each level to generate a health status. It also indicates potential points of failure, such as signal loss or noise, and the importance of designing for resilience. In summary, it illustrates the benefits of multimodal integration for accuracy and robustness.

Recent methods tend to be based on deep learning models such as convolutional neural networks (CNNs), LSTM networks, transformers, and hybrid networks [24, 29, 32].

Figure 6 illustrates the comparative strengths and limitations of major multimodal fusion strategies used in wearable healthcare systems. It evaluates data-level, feature-level, decision-level, adaptive, transformer-based, and self-supervised fusion approaches across performance dimensions including accuracy, interpretability, latency, computational complexity, robustness, energy efficiency, and edge suitability. The figure emphasizes that

Figure 5
Hierarchical multimodal data fusion architecture

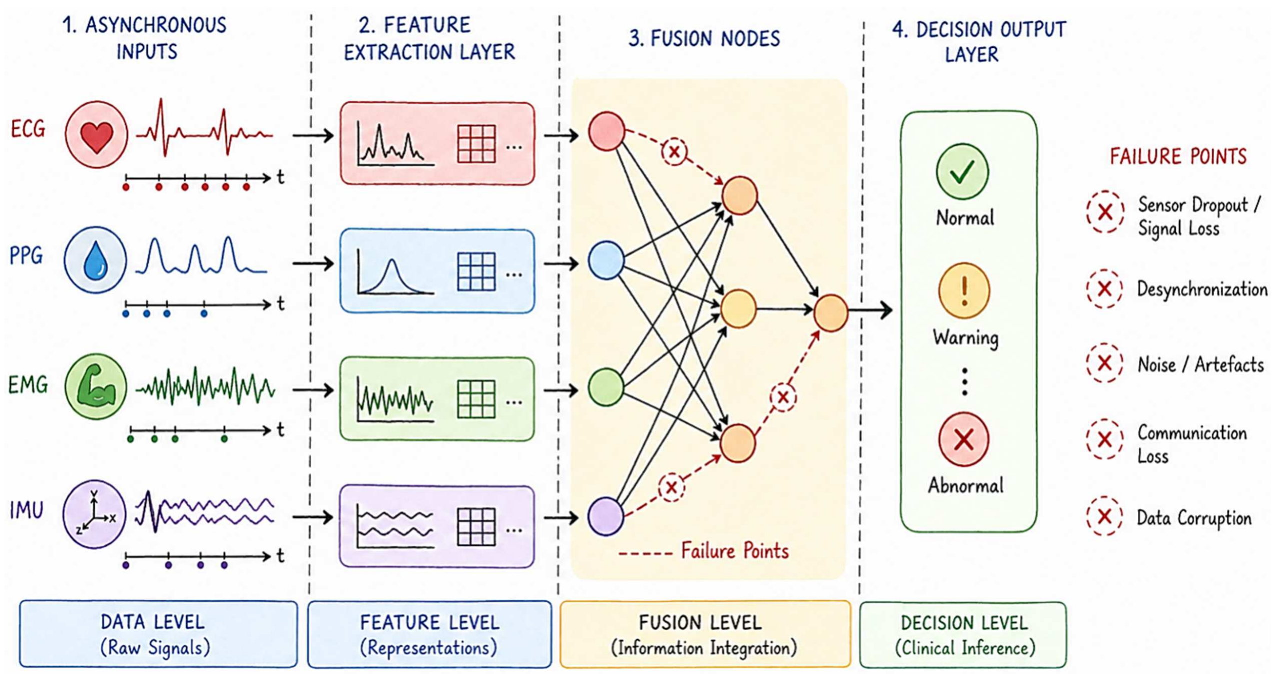
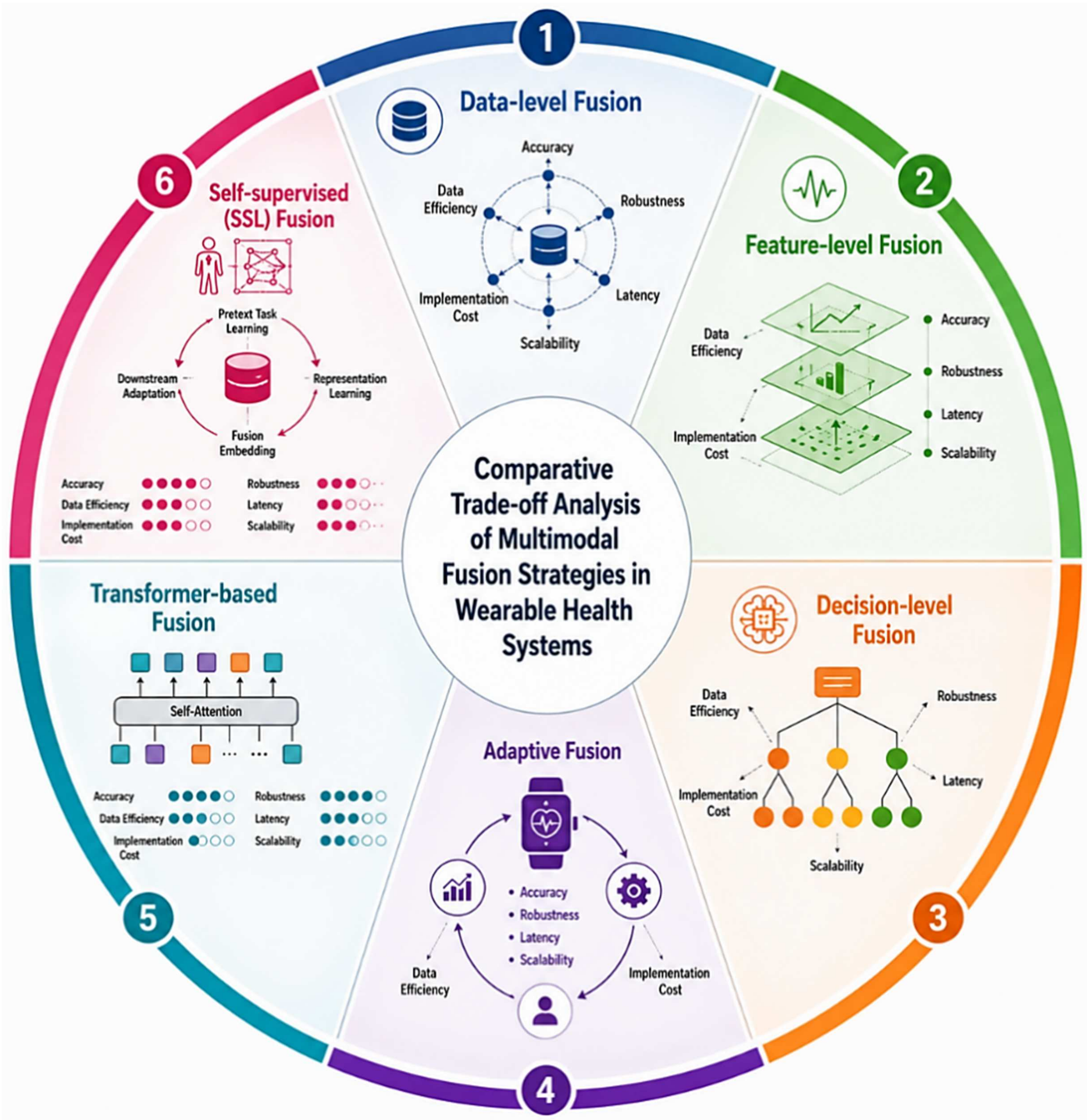


Figure 6
Comparative trade-off analysis of multimodal fusion strategies in wearable health systems



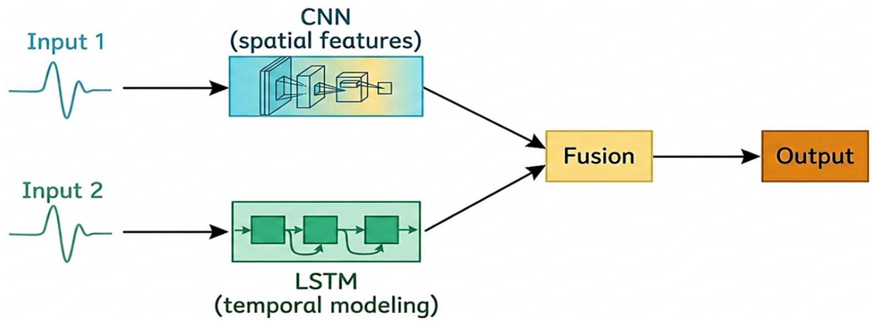
no single fusion strategy optimizes all system requirements simultaneously, thereby highlighting the need for application-specific and energy-aware architectural trade-offs [20, 21, 24, 29].

Figure 7 depicts a hybrid deep learning model used for multimodal data analysis. It shows how CNNs extract spatial features from input signals, while LSTM networks capture temporal patterns. The architecture integrates outputs from different modalities into a unified representation before making predictions. The diagram emphasizes the flow of data through each layer and how combined learning improves accuracy. It provides a clear understanding of how modern AI models handle complex, time-dependent physiological data [5, 17, 29, 30, 32].

These models perform well in the lab, but their performance in real-world scenarios exhibits critical vulnerabilities that are not evident during lab-based benchmarking. A key failure mode is the dominance and collapse of a high-fidelity signal (often ECG or accelerometers) that dominates model predictions and suppresses other less dominant modalities, such as PPG or EMG. This decreases information diversity and susceptibility to sensor failure. This means fusion does not improve robustness but centralizes decision-making in a limited feature space, reducing robustness [23, 28]. A further limitation is the noise amplification that takes place during the nonlinear fusion. Deep models embed multimodal signals into a common latent space without specific disentanglement of noise, allowing noise from one modality to transfer to the other modal feature spaces. This makes it a significant problem in the case of biosignals where noise is correlated and physiologically relevant, rather than purely random [29, 33].

Deployment also presents distributional shift and population variability, in which models trained on single populations

Figure 7
Deep learning multimodal fusion model (CNN–LSTM hybrid)



(age, race, physiology) do not generalize across populations. Skin pigmentation, cardiovascular status, and motion dynamics significantly influence the signal shape, particularly in PPG and inertial sensors. This requires domain adaptation and representative data collection for fair and equal performance across the population [1, 34, 35]. Furthermore, data imbalance and lack of long-term coverage continue to be major challenges. The majority of existing datasets are limited in size, duration, and laboratory-based nature, hindering the capacity of models to learn long-term physiological shifts, behavioral adaptation, and rare physiological (pathological) events. This leads to misleading estimates of performance metrics that do not correlate with real-world performance [2, 4]. One critical but under-investigated aspect is intermittent failure modes, such as asynchronous sensor failure, partial signal degradation, and power-related disruptions. Wearable systems often operate with missing or corrupted inputs due to motion artifacts, device removal, loss of contact due to sweating, or loss of connectivity. Unfortunately, many fusion systems implicitly rely on continuous and simultaneous input streams, resulting in a sudden drop in performance when this is not the case [24, 31].

In real-world applications, contemporary dynamic fusion systems cope with asynchronous dropouts via time-varying reliability assessments. Time-varying reliability scores are applied to each modality, based on signal quality measures, reconstruction error, or learned uncertainty. As a sensor (e.g., PPG signal) becomes unreliable due to motion or loss of optical contact, its influence in the fusion layer is gradually reduced rather than abruptly cut off. At the same time, other modalities such as IMUs or ECG raise their weight in the fusion layer, ensuring continuous predictions. When a sensor is completely lost, probabilistic fusion, attention-based gating, or redundancy-aware designs enable the system to gracefully degrade to a reduced-modality operation. This facilitates graceful degradation, rather than a catastrophic failure, important for wearable applications under sparse sensing conditions.

These limitations are related to the mismatch between the design assumptions of the algorithms and the real-world environment from a systems engineering perspective. New approaches, such as SSL and multimodal foundation models, are being explored to tackle these issues using large-scale unlabeled physiological data to enhance resilience and generalization [2, 23]. SSL allows representation learning from continuous physiological signals like ECG, PPG, and EEG, eliminating the need for large labeled datasets and enhancing detection of rare events.

Likewise, novel fusion approaches such as modeling of uncertainty, adaptive weightings, and attention mechanisms are under investigation to address the effects of modality failure and robustness to poor signal quality. But these methods should be thoroughly tested in real-world ambulatory, rather than laboratory, settings for clinical validation.

Finally, the integration of multimodal wearable systems into clinical practice introduces new constraints on regulatory, interpretability, and ethics [36–41]. Adaptive learning systems must bridge dynamic model evolution and static regulatory approval processes (Software as a Medical Device (SaMD)), resulting in a disconnect between the pace of innovation and the stability of medical device certification. On the other hand, multimodal fusion in wearable health technologies is limited not just by the model size but by the instability of the system in the real world. Advancement in this space needs to be achieved by shifting the focus from accuracy-driven optimization to resilience-driven engineering, where resilience to failure, interpretability, and operational continuity in the face of uncertainty are considered as engineering constraints.

5. System-Level Design Considerations

Multimodal sensing and AI-based data fusion can only be effective as far as the system architecture in which it is deployed is. The wearable health technologies do not consider system-level design; system-level design is a limitation. The deployment of intelligence is influenced by latency, energy needs, the ability to process, and data protection needs. Disciplined engineering choices in processing architecture, power management, embedded implementation, and security frameworks are important to provide the transition from laboratory prototypes to clinically credible and scalable products.

5.1. Edge versus cloud processing

The where question of wearable health systems is connected to one of the main architectural questions of wearable health systems. The former is referred to as edge processing, to execute analytics on the wearable device or a local gateway, and the latter as cloud processing, where the data are transmitted to the remote servers to execute models and store them. Edge processors have decisive advantages in latency-sensitive applications such as arrhythmia detection, fall detection, or seizure monitoring. By performing inference locally by systems, the delays caused by the transmission are reduced to the least, and immediate response is achieved nearly instantly. Privacy is also promoted with edge architectures, whereby sensitive physiological data do not necessarily have to be sent to external servers continuously [42, 43]. In addition, low-energy cost is realized by cutting back on energy consumption incurred in wireless communication. The memory, processing capability, and battery capacity, however, limit the edge devices. Complex deep learning models may use up all the available computational resources unless optimized. Cloud processing, on the other hand, assists high level of computation and massive data aggregation. It allows refining of the model continuously with population-level datasets and allows longitudinal health analytics. The trade-off is that of more latency, more bandwidth usage, and increased exposure to privacy.

In reality, hybrid architectures are taking the form of the dominant paradigm. The edge is used for lightweight inference to enable real-time responsiveness, and the cloud is used for model training, periodic model updates, and advanced analytics. The technical challenge is to intelligently distribute the workloads so as to achieve the balance between response time, privacy, and energy efficiency.

5.2. Energy efficiency and power management

Energy continues to be a limitation of wearable systems. The form factor and comfort directly depend on the size of the battery, but the constant sensing, wireless transmission, and AI inference use a lot of power. In hardware design, low-power design is thus a fundamental one. Baseline consumption is minimized by ultralow-power microcontrollers, energy-efficient radio transceivers, and energy-efficient analog front ends. Battery life is also extended by the use of duty cycling strategies where sensors and radios are only switched on at times when they are in use. On the algorithmic level, there are necessary model compression techniques [44, 45]. Pruning removes the unnecessary connections in the neural network; it not only results in a significant decrease in accuracy but also enables one to reduce the computational load. Quantization decreases the numerical precision like 32-bit floating-point parameters to 8-bit integers, which decreases the memory footprint and inference cost. Knowledge distillation is an approach to learning that transfers knowledge of large models to small student networks, which can be deployed on the edge. AI design cannot be made energy aware. A clinically precise model that depletes a battery in hours is commercially and medically unviable. In the co-design of hardware and algorithms, designing sustainable wearable intelligence is required.

5.3. Real-time constraints and embedded implementation

Wearable health systems are frequently subject to severe, strict real-time constraints. The diagnosis of irregular heartbeats or sudden falls involves a conclusion within milliseconds to several seconds. Predictable processing latency, deterministic timing, and constant throughput are thus requirements. Embedded implementation normally uses microcontrollers that have limited memory and clock speed. The most recent developments in specialized AI accelerators and neural processing units have increased inference capacity on devices, allowing the use of relatively complex neural networks without necessarily having to be connected to the cloud all the time. One of the critical developments is the advent of the so-called TinyML, which are ML models that are optimized to run on microcontroller-class devices. SmallML systems feature small architectures, fewer parameters, and high-performance inference pipelines that are optimized to run on small embedded systems [46, 47]. It needs close memory management, fixed-point arithmetic optimization, and lean data pipelines to be successfully implemented. Other aspects that lead to system reliability are synchronization among sensors, strong interrupt processing, and fail-safe design. Wearable platforms should be embedded to be able to operate steadily in the fluctuating physiological and environmental environments.

5.4. Data security and privacy

The physiological information is very intimate. The heart rhythms, neural patterns, biochemical markers, and behavioral signals are sensitive health information that is regulated. Both security and privacy cannot be retrofitted and must be included in the system architecture.

Encryption protocols are used to encrypt data in the transmission of information between sensors, the gateway, and cloud servers. The cryptographic algorithms must be lightweight to maintain the energy levels and offer security. Risks of interception or spoofing are prevented by the use of secure communication layers in WBANs. Federated learning has been one of the intriguing approaches of privacy-preserving AI [48, 49]. Instead of transmitting raw data to a central server, the models are trained on locally processing devices, and the update of parameters is exchanged only. This approach reduces the exposure of the health information at the individual level, and it supports the education at the collective level of distributed populations. Besides the technical protection, there is a need to have clear data governance and compliance with the health data regulations in order to reach clinical integration. Trust is not purely a social notion; it is an aim of technical designs. To conclude, system-level design factors dictate whether multimodal AI-powered wearable technologies would continue being experimental technologies or evolve into dependable healthcare infrastructure. Processing architecture, power management, embedded intelligence, and data security interact to determine the viability of the next-generation wearable health systems.

6. Clinical and Application Domains

The clinical utility of multimodal sensing and AI-driven data fusion is not determined by the beauty of algorithms but by clinical utility. Wearable health technologies are actively being postulated as a continuation of medical infrastructure, which helps to make early diagnoses, engage in continuous monitoring, and provide personalized intervention [34, 35]. But performance claims should be scrutinized, and attention should be focused on the data quality, validation, and trans-translational readiness. The quality of approaches used in cardiovascular, neurological, rehabilitative, and chronic disease monitoring is highly variable.

6.1. Cardiovascular monitoring

Cardiovascular monitoring is the most mature and commercially available application of wearable technologies [28, 50]. Multimodal approaches using ECG, PPG, and motion sensors are common to improve accuracy for ambulatory monitoring [25, 51]. Much research has been conducted into the detection of arrhythmia, including atrial fibrillation, with ECG and PPG fusion models [10, 52]. The use of deep learning has been claimed to yield classification accuracies of over 95% in controlled settings [16]. However, these studies often use selected public datasets, such as the MIT-BIH Arrhythmia Database, which may not represent motion artifacts, population diversity, and noise levels [52]. Cross-dataset validation with diverse datasets is often lacking [53]. Wearable cuffless blood pressure systems have also been explored, combining PPG morphology, pulse transit time (ECG-derived), and motion information [31, 50]. Despite reported mean absolute errors being within experimental limits, reproducibility in everyday life is an issue due to calibration requirements and individual variability [31]. Regarding validation, cardiovascular monitoring has the advantage of robust clinical references (e.g., traditional ECG) [10]. But there is an urgent need to shift toward large-scale prospective validation studies across a wide range of demographic groups to ensure clinical validity and generalizability [54].

6.2. Neurological and mental health monitoring

Multimodal wearable systems are increasingly being used for neurological and mental health monitoring [35]. Typical multimodal signal combinations in the detection of cognitive states, stress, and seizures include EEG, heart rate variability (HRV), electrodermal activity, and motion [27]. For stress detection, the combination of physiological signals, including HRV, skin conductance, and accelerometry, is commonly used, with reported accuracy ranging from 80% to 95% based on the size of the dataset and the level of control in the experiment [2]. But a common problem is the use of lab-based stress induction, which lacks ecological validity. Furthermore, subjective self-reports are used for ground truth labeling, impacting model performance.

For seizure monitoring, wearable systems using EEG or multimodal biosignals can achieve high sensitivity in laboratory conditions [55]. However, they suffer from high false positive rates, especially in unstructured environments with greater signal noise and artifacts. Limited data also hamper development, with clinically validated datasets typically being small in size, limiting the ability to generalize and optimize models for different patient cohorts.

In neurological tasks, the multimodal and large datasets that are publicly available are limited, limiting reproducibility. Cross-validation within the same cohort is often used as a validation procedure and not as an actual external test, and this is a cause of concern to overfitting.

6.3. Activity recognition and rehabilitation

One of the oldest fields of wearable sensing is activity recognition, which is mostly powered by IMUs. The type of posture, locomotion, and exercise is classified by multimodal methods or accelerometry and gyroscopy data, with or without EMG data or heart rate data. Convolutional and recurrent deep learning architectures have regularly attained better than 90% on benchmark datasets, such as University of California, Irvine Human Activity Recognition (UCI HAR) dataset [56]. However, these datasets tend to be structured activities, which are carried out by small age groups. Less is usually evaluated in generalization among older populations of people, people with mobility problems, or people with other cultures. Gait analysis and muscle activation monitoring can be used in the recovery process of post-stroke as well as the orthopedic examination in a rehabilitation setting [57]. The most widespread performance measures are the classification accuracy, F1-score, and the confusion matrices. Nonetheless, classification performance should not be confined to clinical significance, but improvements in functional outcomes and patient compliance should be addressed as well. The use of cross-subject evaluation and real-world trials in the validation of rehabilitation research is growing; however, benchmarking protocol standardization is still underway. Cross-study comparisons are complicated by the use of heterogeneous sampling rates and location of the sensors.

6.4. Chronic disease management

Chronic disease management represents one of the most significant application domains of multimodal wearable health systems, particularly for conditions requiring continuous monitoring and early intervention such as diabetes, heart failure, and chronic respiratory diseases [50]. These systems are in line with the concept of preventive healthcare through the longitudinal monitoring of physiological trends and predictive clinical decision-making. In diabetes, wearable continuous glucose monitoring systems are now complemented with physiological and behavioral data such as heart rate and activity for improved prediction of glucose variability [58]. Multimodal integration strategies that combine glucose, motion, and HRV have been shown to hold promise for the prediction of hypoglycemia events with sufficient lead time, though the long-term stability and generalizability across a range of patients remain a challenge [59, 60].

In cardiovascular health, wearable sensor technologies facilitate early identification and tracking of heart failure progression by continuously analyzing HRV, activity levels, and physiological variability. These methods allow early detection of the risk of decompensation, but their clinical use is hampered by variability among patients, sensor devices, and the lack of large-scale longitudinal studies [50]. Likewise, in lung diseases like chronic obstructive pulmonary disease, wearable sensors using motion sensors, respiratory acoustics, and PPG-derived features have demonstrated the potential to detect exacerbations. But current research is constrained by limited sample size and limited clinical validation, which limits its generalization to the broader population [46]. In all applications for chronic disease, a key limitation remains the use of short-term data, limiting the assessment of longitudinal disease progression and model robustness. As a result, large-scale clinical applications will require large-scale longitudinal studies, data diversity, and robust real-world validation protocols.

6.5. Comparative analysis of metrics, datasets, and validation protocols

The variability of the metrics and data state reported in the studies is typical of the multimodal wearable health systems use cases. The most frequently used measure is accuracy, but it is less informative, particularly when working with unbalanced data. Sensitivity, specificity, F1-score, and area under the curve are more descriptive measures that provide more information on model performance but are not always reported. This paradox makes it hard to compare studies with each other and to really assess the model's performance. A key problem is the datasets used for model development and evaluation. Many studies employ controlled or public datasets, which are often small and not representative of the population. These datasets usually do not capture real-life challenges such as motion artifacts, background noise, and variability among individuals. As a result, models that perform well in controlled environments may not perform well in independent or real-world environments, questioning their generalizability and usefulness in clinical practice. Data are still a structural problem. Clinical datasets are also not easily accessible for independent validation, and public datasets are generally small and unidimensional. As a result, most studies use the same dataset for cross-validation, which is prone to overfitting and limits the generalizability of the results. Further, the model's performance is also overestimated due to publication bias toward positive findings, which masks flaws.

Further problems are caused by methodological variability. Variations in data preprocessing, signal segmentation, and feature extraction make it difficult to replicate and to fairly compare studies. In the majority of cases, the performance improvements reported are more related to optimization of the methodology rather than clinical benefits, thus creating a gap between technical and clinical success. To advance to clinical maturity, the field should aim to develop standardized models of assessment, multicenter datasets, and transparency. The need is to move away from performance gains and to focus on generalizability, reliability, and clinical benefit. This is not just a technical shift, but a strategic shift to the things that are important in the real world.

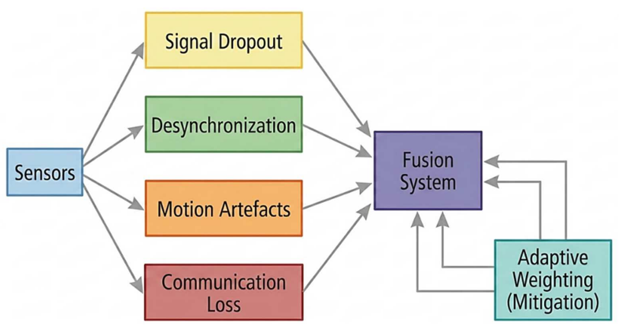
While the performance of such systems in terms of classification accuracy, sensitivity, and reliability demonstrates their technical potential, their true value is in the scalable, reliable, and clinically validated deployment. In the future, a balance of innovation and validation is needed, where technical advancement is complemented by methodological rigor and a clear and measurable effect on patient outcomes.

7. Current System Challenges

Despite the progress in multimodal sensing and AI-inspired data fusion, the field is constrained by technical, clinical, and socio-regulatory issues. Models that have been reported to work in a controlled environment are likely to fail in the real world. These problems need to be addressed to translate the possible models into a reliable healthcare system.

Figure 8 shows common failure modes of multimodal wearable systems. It illustrates how problems like sensor misalignment, motion artifacts, signal dropout, and noise can impact data. It shows how these issues can affect the processing and fusion stages, impacting the final predictions. It also underscores the need for adaptive strategies to ensure system robustness. The figure illustrates these issues to highlight the importance of design and fault management in practice [5, 24, 29, 34].

Figure 8
Failure modes in multimodal wearable fusion systems



7.1. Sensor heterogeneity and calibration

Multimodal wearable systems are systems that co-locate sensors with different sampling frequency, signal amplitude, dynamic range, and physical location [61]. The response of ECG electrodes on the chest is very different from that of PPG sensors on the wrist or EMG sensors on textiles. The shape of the signal can be different although it is in the same modality of the device due to the fixed specification of the device. Calibration is an engineering challenge. Optical sensors need to be aligned and compensated for skin tone; the electrical sensors are prone to contact impedance and sweat. Over time, drift is caused by material degradation and fatigue, which alter the signal characteristics. The heterogeneity that is not removed in multimodal fusion pipelines can cause bias in the distribution of features and worsen the performance of the models. Between manufacturers, standardized calibration procedures are not highly developed. Lacking harmonization, cross-device interoperability will be challenging, and AI trained on a given hardware platform can perform poorly on a different platform. Powerful calibration plans, automatic signal quality assessment, and adaptive correction algorithms are henceforth the powerful aspects of scalable system design.

7.2. Data imbalance and limited clinical datasets

The blood of the AI development is good-quality clinical data, which are, however, lacking in wearable health studies. There are numerous publicly available datasets that are small, gathered in a controlled laboratory, and lack demographic diversity. Rare pathological effects, for example, specific arrhythmias or epileptic seizures, are critical problems of the imbalance of classes in the SSLs. The asymmetry in the data distorts the training dynamics, leading to high overall accuracy but poor sensitivity to minority classes of clinical interest. The problem can be partially solved using the methods of oversampling, synthetic data generation, and cost-sensitive learning, however, using real representative data.

Also, there is a paucity of longitudinal data. The evaluation of the stability and progression of chronic diseases takes months or years of constant records. Short-term datasets do not allow testing of temporal drift, behavioral adaptation, and artifacts of device wear. In the absence of large-scale, multicenter, multimodal data, claims of general applicability can only be tentative.

7.3. Generalization across populations

Wearable health systems must be functional in age, ethnicity, physiological conditions, and lifestyle situations. However, a high number of models are trained using homogeneous cohorts that include a lot of young and healthy individuals. The difference in physiological baselines between populations is a result of genetics, comorbidity, medication, and environment. The issue of generalization manifests itself as models that are trained in a single demographic setting are not able to continue to perform in a different setting. To illustrate, the quality of the PPG signal and morphology may vary depending on the pigmentation of the skin and the peripheral circulation, which affects the heart rate and blood oxygen estimates. The patterns of motion in different age groups vary and affect the accuracy of activity recognition.

The strategies of domain adaptation and transfer learning are being developed in order to deal with cross-population variability. However, when training on diverse data and inclusive validation processes are done, sound generalization is ultimately achieved. Healthcare technology is not provided in a way that is equitable; it is a technical requirement.

7.4. Regulatory, ethical, and data acquisition pathway considerations

Regulatory and ethical governance represent critical determinants in the translation of wearable health technologies from experimental prototypes to clinically deployable systems. As multimodal systems move toward diagnostic and therapeutic applications, they are subject to rigorous regulatory oversight such as the SaMD regulation of the Food and Drug Administration (FDA) in the USA and the Medical Device Regulation (MDR 2017/745) in the European Union (EU). These guidelines demand analytical validity, clinical validity, and performance for systems that impact clinical decision-making [39]. But a critical methodological consideration is required with regard to data acquisition in wearable system validation. Unlike large-scale human subject experimental studies, many modern wearable health studies are based on specific clinical data streams. These streams generally involve passive monitoring, observational cohort data, retrospective data, or low-invasion signal acquisition. These designs are deliberately chosen to minimize regulatory burden while still being relevant to clinical needs, thus enabling expedited regulatory approval and deployment. This is important since the regulatory pathway is highly sensitive to the classification of study design. Human subject experiments with active manipulation of physiological processes demand rigorous ethical review and multiple stages of clinical trials. On the other hand, observational deployments of wearables that passively gather biosignals in natural settings may be classified as lower risk, allowing for more efficient ethical and regulatory approval processes with review boards and regulatory bodies.

Moreover, today's adaptive ML algorithms pose further challenges due to ongoing updates. This complicates static approval models, requiring new regulatory approaches such as lifecycle regulation and Predetermined Change Control Plans (PCCPs) that enable controlled updates of algorithms without recertification if performance limits are established. Ethical considerations also go beyond safety, encompassing informed consent, fairness, data governance, and transparency of automated decision support systems. Wearable datasets are often longitudinal and sensitive; therefore, strong governance frameworks are needed to safeguard privacy and ensure model performance across a population.

In summary, successful regulatory translation of wearable AI systems requires not only adherence to medical device regulations but also an understanding of the data collection strategies. Differentiating between interventional clinical experimentation and targeted observational data collection is essential for realistic deployment timelines and scalable system design.

7.5. Long-term wearability and user compliance

The most innovative multimodal system will not work even when the users are not using the device on a regular basis. The most important factors of long-term compliance are comfort, esthetics, battery life, and perceived value. Large machines, frequent recharge requirements, and contact dermatitis do not add to the interest in the long term.

The signal quality is also influenced by the user's behavior. The loss of sensors or lack of sensors at some instances or at removal during sleep will cause gaps in the data and inconsistency. Multimodal fusion algorithms will thus have to take complete or corrupted streams of input into consideration. There is also psychological acceptance that is contributing. Wearable monitoring will be more adhered to when feedback is comprehensible and implementable. The systems, which give many false alarms or ambiguous messages, face the risk of being switched off. In terms of engineering, the ergonomic design, breathable materials, low-profile integration, and long battery life are required for long-term wearability. Systems-wise, adaptive algorithms with intermittent information are also of paramount importance. Technical heterogeneity, absence of data, impediments to generalization, regulatory scrutiny, and human factors are among the factors that drive the direction toward clinically robust multimodal wearable health systems. To overcome these issues, multidisciplinary approaches, hard validation, and design principles based on the reality constraints and not on the laboratory optimization are needed.

7.6. Multimodal fusion in high-noise and extreme operational environments

Existing multimodal wearable health systems are usually designed and tested in a laboratory or semi-laboratory environment. But current deployment of these systems increasingly occurs in extreme motion, mechanical stress, and signal distortion environments. These range from aerospace monitoring under high acceleration, defense applications under ballistic impact, to extreme sports applications where biomechanical transitions take place during contact, collision, or high-performance activity. In these environments, multimodal biosignals acquired from ECG, PPG, EMG, and IMUs are prone to nonlinear distortion, motion artifacts, sensor saturation, and loss of signal [62]. Such conditions break the assumptions of stationarity and low noise that are typically considered when developing models. Consequently, data fusion algorithms that are effective in clinical monitoring may suffer performance degradation, feature instability, and elevated false alarms in these extreme conditions.

Wearable systems for extreme environments also present challenges due to rapid sensor orientation changes, skin contact pressure variations, and transient physiological effects such as tachycardia and muscle activation. This introduces intermingled noise and signal components, which cannot be removed by conventional denoising techniques. As a result, robustness in multimodal fusion needs to be considered not only in terms of noise reduction but also in terms of distributional robustness and dynamic signal distortion. Recent research efforts are starting to overcome these challenges by developing domain-adaptive multimodal fusion models, physics-based signal reconstruction, and robust neural architectures that are stable under extreme motion. In parallel, novel sensor technologies such as flexible strain sensors, hydrogel-based biomechanical sensors, and impact-resistant textile-embedded sensors are being developed for applications in extreme conditions, such as sports biomechanics and aerospace health monitoring.

These extreme scenarios must be taken into consideration when assessing the generalizability of multimodal AI systems. Without testing under noisy conditions, claims of system performance are restricted to laboratory conditions and may not be suitable for mission-critical or safety-critical applications.

8. Research Frontiers and Emerging Directions

The next phase of multimodal wearable health systems is increasingly characterized by a paradigm shift from performance-driven to constraint-driven system engineering. Wearable systems are constrained by limited energy, heat, computational capacity, and physiological acceptability, in contrast to traditional ML settings. Consequently, new research endeavors should not be viewed in isolation, but as interlinked elements of a physically constrained WBAN environment.

8.1. Self-supervised and foundation models for physiological intelligence

SSL allows representation learning from large-scale physiological data streams (ECG, PPG, EEG, IMU) without the need for large-scale annotations [14, 53]. This enhances data efficiency in multimodal wearable systems, but its use within wearable nodes is inherently limited by the power constraints of WBAN and computational constraints of wearable devices [63, 64]. Wearables typically have a milliwatt-level power budget, in which continuous inference with transformers is physically impossible due to both computational and thermal constraints [56, 65]. Thus, foundation models cannot be directly deployed in wearables. Instead, a multi-tiered approach is needed where local feature encoders are used to extract features, but higher-order representation learning is outsourced to edge or cloud computing platforms [66, 67].

This design is in line with energy-efficient IoT healthcare systems where computations are distributed based on device power budgets, rather than model ambition.

8.2. Multimodal large models and cross-modal clinical intelligence

Multimodal large models combine wearable biosignals, electronic health records, and other clinical information to enhance predictive decision-making [16, 68]. But in WBANs, the limiting factor is not model size but energy and bandwidth for communication [35, 69]. Body area network wireless communication is much more energy-intensive than local processing, especially when streaming high-frequency biosignals. This results in a data need versus energy trade-off for large model-based intelligence on wearable devices. As such, practical clinical applications must be based on compressed latent features and event-driven feature transmission, rather than streaming [59, 70]. This enables multimodal intelligence systems to work within the energy budget without compromising accuracy.

8.3. Digital twins and personalized physiological modeling

Digital twins offer dynamic computational models of individual physiological states with real-time data from wearable sensors [22, 71]. But continuous wearables-to-digital twin synchronization introduces considerable energy and communication costs in WBANs. Biologically, wearable systems are limited by the amount of energy that can be harvested from the human body. Biomechanical and thermoelectric energy-harvesting technologies typically generate only microwatt to low milliwatt levels of power in practical settings [35, 56]. This is not enough to support continuous high-frequency updates to digital twins. As a result, digital twin systems need to be updated in an event-driven fashion, where state estimation occurs upon clinically significant physiological changes, rather than in a continuous fashion. This method is less power-hungry while still providing clinically relevant temporal resolution as at when due.

8.4. Advanced functional materials for integrated and visual-encoded wearable sensing

Materials engineering is increasingly driving wearable sensing to embed sensing into physical and optical properties, rather than purely electrical signal processing. Traditional conductive polymers and graphene electrodes are still the basis of flexible bioelectronics, but they rely on continuous electrical signal acquisition, conditioning, and processing, which adds to the system complexity and power consumption [31, 32, 34].

Mechanochromic materials are a significant advancement that translates strain, pressure, and twist into color changes. This allows direct visual monitoring of biomechanical activity, eliminating the need for an electrical intermediary. But their use is constrained by hysteresis, drift, and temperature/humidity sensitivity, which hinder measurement stability in long-term applications. Structural color sensors, such as photonic microstructures, offer high sensitivity to strain through interference-induced color changes. Although mechanically robust in the lab, it is very susceptible to microstructural deformation and refractive index variations under repeated strain, which limits its use for monitoring [32, 34]. Hydroxypropyl cellulose hydrogels and other biointegrated polymers provide soft tissue interfaces for sensing via biocompatibility and flexibility. They allow for coupled mechanical and optical responses for strain and hydration sensing. However, dehydration and time-dependent mechanical changes pose stability limitations for uncontrolled environments [31, 33].

New device form factors such as smart contact lenses and mechanochromic sutures bring sensing to high-sensitivity anatomical and surgical applications. Contact lenses allow for monitoring of intraocular pressure and corneal shape but are limited by tear film and biofouling effects. Mechanochromic sutures offer visual cues of tissue tension but are semi-quantitative and environmentally sensitive [31, 34].

Overall, these materials redefine wearable sensing into hybrid systems where optical and mechanical encoding is not only used to replace electronics but also to complement them. Electronic components are still required for high-precision sensing, but new materials minimize sensing costs in specific applications and enhance spatial physiological interpretation.

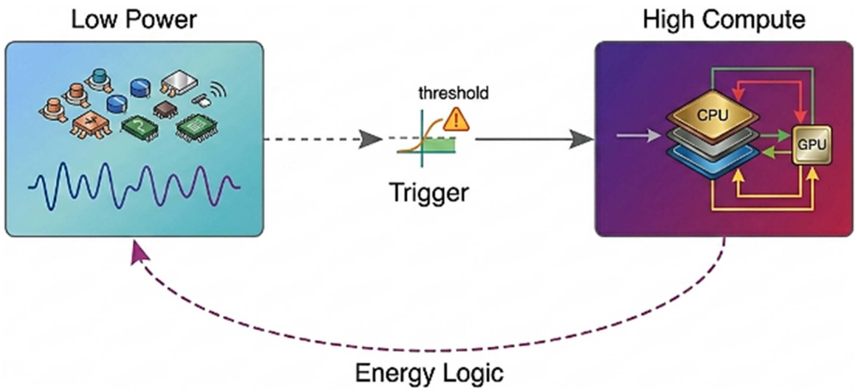
8.5. Event-driven and window-based visualized monitoring in resource-constrained wearable systems

The integration of advanced connectivity paradigms such as 6G, digital twins, and foundation models into wearable health systems must be interpreted through the strict physical and energetic constraints of WBANs. While these technologies offer powerful capabilities for ultralow-latency communication, real-time system mirroring, and large-scale contextual inference, their deployment in wearable environments is fundamentally limited by energy availability, thermal dissipation capacity, and on-device computational budgets [42, 43, 46, 47].

In practical WBAN architectures, continuous reliance on high-bandwidth 6G communication or persistent cloud-synchronized digital twin models is not feasible without violating battery endurance and thermal safety thresholds. Each transmission cycle and inference exchange introduces nontrivial energy cost, making unconstrained use of these paradigms incompatible with long-duration physiological monitoring. Therefore, these systems must be reformulated as intermittent, event-triggered services rather than continuous operational layers.

Figure 9 illustrates the shift from continuous monitoring to event-driven operation in wearable systems. It shows a low-power baseline mode where signals are lightly monitored and a trigger mechanism that activates full processing during critical events. The diagram highlights how data are captured, analyzed, and summarized within specific time windows. This approach reduces energy consumption while focusing on clinically important moments. It demonstrates how intelligent activation

Figure 9
Event-driven wearable monitoring framework



improves efficiency without compromising diagnostic value or system responsiveness [44–47].

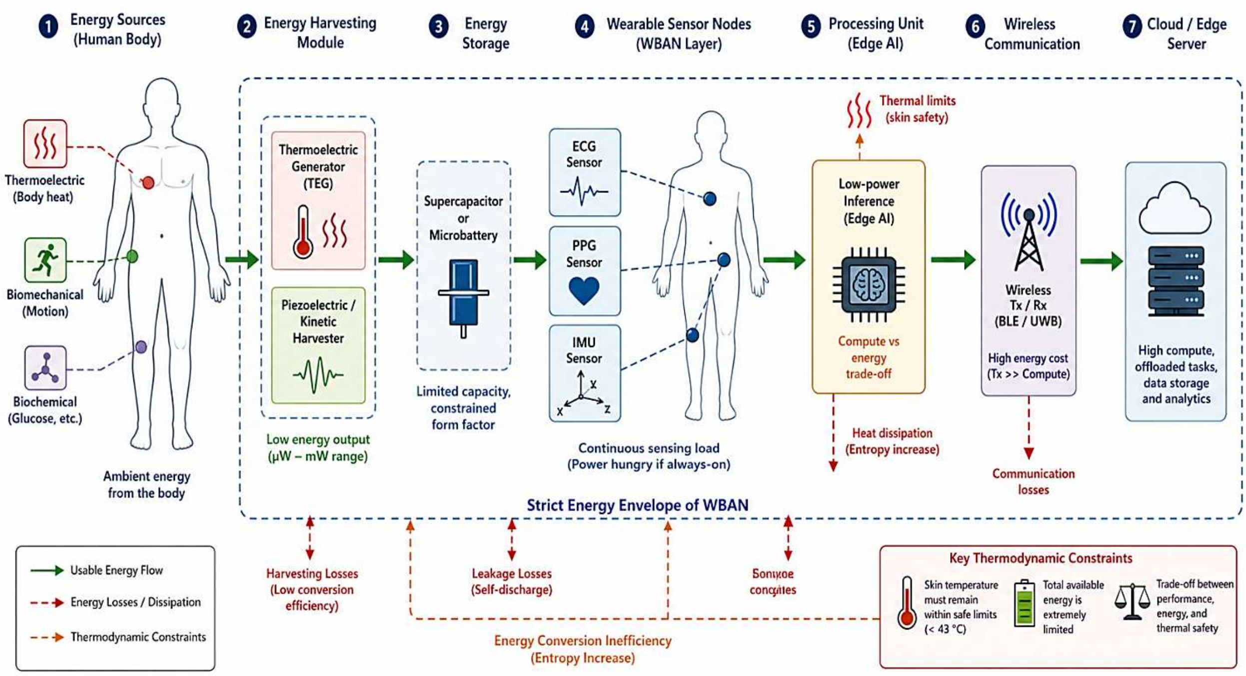
Digital twins, when applied in wearable healthcare, are more realistically implemented as periodically updated physiological mirrors rather than continuously synchronized replicas. Updates are therefore constrained to clinically meaningful windows, where state changes justify communication overhead. Similarly, foundation models are best positioned as hybrid inference engines, where lightweight edge models perform continuous screening while complex model inference is delegated to sparse, high-value events.

This architecture aligns naturally with event-driven monitoring strategies, where sensing, computation, and communication are activated only during clinically significant physiological transitions. Such an approach ensures that computational intensity scales with diagnostic value rather than data volume, thereby preserving energy efficiency and reducing thermal accumulation in compact wearable form factors.

A critical physical limitation underpinning all wearable system design is the thermodynamic constraint of human energy harvesting. Although energy-harvesting techniques, including biomechanical, thermal, and biochemical sources, are often proposed as supplementary power solutions, their output remains fundamentally limited by the low entropy energy gradients available in the human body.

Figure 10 illustrates the energy consumption and management in a wearable body area network. It illustrates the power flow from battery resources to sensors, processors, and communication devices. It illustrates energy losses through heat and the scarcity of energy in small devices. It also shows human body constraints, such as thermal comfort. This diagram illustrates why energy efficiency is important and why system design needs to

Figure 10
Energy flow and thermodynamic constraints in WBAN



consider trade-offs between system performance, sustainability, and comfort [44, 63, 69].

In reality, energy harvesting can only support ultralow power sensing or intermittent communication but cannot support continuous high-bandwidth 6G communication or large-scale model inference. This places a ceiling on system autonomy and requires energy prioritization [62, 63]. As a result, WBAN design should embrace a multilayered intelligence approach that balances sensing, communication, and model inference with energy levels. This involves low-power edge processing for continuous monitoring and higher-order AI functions such as digital twin updates and foundation model inference, which are only engaged under energy-feasible and clinically relevant scenarios.

In conclusion, 6G, digital twins, and foundation models should not be thought of as always-on features in wearable systems, but rather as event-driven and constrained intelligence layers that operate within the bounds of thermodynamics and energy. This perspective ensures that system design is physically feasible, energy efficient, and clinically viable in real-world settings.

8.6. Extreme environment and high stress multimodal wearable systems

The operational environments of wearable systems include not only clinical or laboratory settings but also extreme conditions involving high acceleration, vibration, and stress. These range from space monitoring to military deployment and extreme sports. In these scenarios, sensor fusion systems need to work under extreme noise and distortion. For instance, high acceleration environments may cause motion artifacts, which can significantly distort ECG and PPG signals, while IMUs can still function but exhibit nonlinear motion distortion [63, 64].

In addition, in adventure sports, the incorporation of hydrogel or flexible strain sensors in the sports equipment facilitates dynamic pressure distribution and biomechanical analyses during acceleration and deceleration. But these signals may be asynchronous and partially degraded; thus, temporal alignment and uncertainty-aware sensor fusion mechanisms are needed.

Existing AI sensor fusion approaches are not robust in such scenarios due to the assumption of complete signals and stationarity. This challenge can be addressed with noise-robust architectures, physics-based filtering, and redundancy-aware sensor fusion strategies that explicitly account for sensor failure modes [29, 72].

8.7. Regulatory, clinical translation, and data acquisition pathways

The development of wearable AI systems for clinical use is tightly regulated, with regulatory guidelines that differ between countries (SaMD in the USA and Medical Device Regulation (MDR 2017/745) in the EU) [39, 62, 73]. One of the important differences in validation approaches today is between human experimental studies and clinical data streams. Current approaches to wearable validation rely heavily on structured clinical data collection streams from controlled observations to invasive or interventional human experimentation. This practice allows quicker regulatory fit while ensuring ethical standards and simplifying certification [63, 74]. But adaptive AI systems, which continually learn from data, create regulatory complexity as a result of model drift and changing performance. This presents a challenge to static regulatory approval models and requires lifecycle-based regulation and post-market surveillance [40, 41]. Emerging regulatory frameworks are likely to embrace adaptive certification schemes with pre-specified change control procedures to ensure that algorithm updates are traceable, auditable, and safe while enabling technological evolution.

Thus, it provides a converging perspective of wearable health systems moving toward adaptive intelligence ecosystems. The combination of SSL, multimodal foundation models, digital twins, functional materials, event-driven monitoring, extreme environment sensors, and regulatory frameworks is a transition from passive monitoring to active physiological intelligence systems. But this shift is constrained by energy, signal, data, and regulatory constraints. The next steps require a balance between computational, physical, and clinical considerations.

Table 1 [36–41] provides an overview of regulatory and clinical translation frameworks around the world in relation to AI-enabled wearable health systems, which include device classification, validation requirements, continuous learning policies, regulatory priorities, and limitations. It compares such fixed models as FDA SaMD and CE-MDR with new adaptive AI models,

Table 1
Regulatory and clinical translation frameworks for AI-enabled wearable health systems

Regulatory framework	Region	Device classification	Validation requirements	Continuous learning policy	Key regulatory focus	Main limitation
FDA SaMD Framework	United States	Risk-based (Class I–III software as medical device)	Analytical validity, clinical validation, real-world performance evidence	Generally static approval; updates require re-validation or prior approval	Patient safety, clinical efficacy, risk mitigation	Limited flexibility for adaptive/continuously learning AI models
CE-MDR (EU 2017/745)	European Union	Risk-classified medical software (Class I–III)	Clinical evaluation, technical documentation, post-market surveillance	Restricted post-market algorithm changes without regulatory notification	Safety, traceability, clinical benefit	Slow approval cycles and high documentation burden

(*Continued*)

Table 1
(*Continued*)

Regulatory framework	Region	Device classification	Validation requirements	Continuous learning policy	Key regulatory focus	Main limitation
IMDRF SaMD Framework	International (Guideline)	Software as Medical Device (risk categorization model)	Lifecycle-based evidence generation and clinical performance monitoring	Encourages lifecycle management but not legally binding	Harmonization of global SaMD regulation	Non-binding framework; inconsistent adoption across regions
FDA AI/ML-Based PCCP (Proposed)	United States (Emerging)	Adaptive AI/ML-enabled medical software	Predetermined change control plan, continuous performance monitoring	Supports controlled algorithm updates under predefined conditions	Safe adaptation of machine learning systems	Still evolving; limited real-world regulatory implementation
Post-Market Surveillance Systems	Global	Applied across all medical device classes	Real-world data monitoring, adverse event reporting, drift detection	Continuous monitoring rather than pre-approval adaptation	Long-term safety and performance assurance	Reactive rather than proactive regulatory mechanism

with a focus on patient safety, efficacy, and post-market surveillance, and the issue of limited flexibility, slow approvals, excessive documentation, and inconsistent adoption globally.

Table 2 [24, 29, 42, 43, 46, 47, 50, 54–56, 66, 72–74] was created through an analysis of studies identified in a systematic review of multimodal wearable health systems. Using a set of inclusion criteria, peer-reviewed articles detailing wearable sensor setups, AI models, and performance results were extracted. For each study, we extracted and documented the sensor modalities, sensor fusion approaches, learning models, datasets, applications, and performance metrics.

When available, computational properties such as number of parameters, model sizes, and inference attributes were extracted from the original publications. However, as most studies do not report hardware-level or efficiency metrics, this introduces variability that makes direct comparisons difficult. To overcome

Table 2
Quantitative benchmark of multimodal AI-driven wearable health systems

Sensors used	Fusion level	AI model	Dataset scale	Application	Performance	Parameters (approx.)	Model size (MB)	Inference complexity (FLOPs or class)	Latency (edge estimate)	Deployment class
ECG, PPG, accelerometer	Feature-level	Support Vector Machine	50 subjects, 24 h	Arrhythmia detection	Accuracy: 92%	NR (kernel-based, low-param model)	<1 MB	Low, O(n^2) kernel ops	5–20 ms	Edge
ECG, PPG, EMG, temperature	Data-level	Random Forest	100 subjects, 48 h	Heart rate monitoring	Mean Absolute Error (MAE): 3 bpm	~10^4–10^5 trees/-params equivalent	~2–5 MB	Low–medium (tree traversal)	10–30 ms	Edge/cloud
EEG, HR, accelerometer	Feature + Temporal	CNN-LSTM	120 subjects, 1 week	Stress detection	F1-score: 0.88	~1–3 million	~8–15 MB	Medium (~10^7–10^8 FLOPs)	30–80 ms	Cloud/ hybrid
PPG, glucose, motion	Hybrid	Ensemble (Gradient + RF)	80 patients, 2 months	Hypoglycemia prediction	Sensitivity: 85%	~0.5–2 million	~5–10 MB	Medium	20–60 ms	Edge + cloud

(*Continued*)

Table 2
(*Continued*)

Sensors used	Fusion level	AI model	Dataset scale	Application	Performance	Parameters (approx.)	Model size (MB)	Inference complexity (FLOPs or class)	Latency (edge estimate)	Deployment class
ECG, motion, temperature, EMG	Multi-level	Transformer-based model	60 subjects, 14 days	Arrhythmia + activity recognition	Accuracy: 94%	~5–20 million	~20–80 MB	High (~10^8–10^9 FLOPs)	80–200 ms	Cloud/edge-assisted
Biochemical, ECG, PPG	Feature-level (self-supervised)	Contrastive SSL model	150 subjects, 1 month	Chronic disease monitoring	AUROC: 0.91	~10–50 million	~50–150 MB	High	100–250 ms	Cloud
ECG, EMG, accelerometer	Adaptive fusion	Weighted linear + ML hybrid	70 subjects, 7 days	Gait analysis	Accuracy: 90%	~10^4–10^5	<3 MB	Low–medium	10–25 ms	Edge
PPG, accelerometer, skin conductance	Featur e-level	CNN + Attention	100 subjects	Stress recognition	F1-score: 0.87	~2–6 million	~10–25 MB	Medium–high	40–120 ms	Edge/cloud
ECG, EEG, motion, temperature	Multi-level	Hybrid CNN-LSTM-Transformer	50 subjects, 2 weeks	Seizure detection	Sensitivity: 92%, Specificity: 89%	~10–30 million	~30–120 MB	Very high (~10^9+ FLOPs)	120–300 ms	Cloud

this issue, approximate computational complexity estimates were derived using well-known architecture-based profiling from ML literature, allowing for consistent classification across different model types. The table was then standardized into consistent computational metrics, such as range of parameters, model size, estimated floating-point operations (FLOPs), and latency of inference on edge class devices. This normalization offers a comparative engineering-focused approach to benchmarking multimodal AI wearable systems under real-world deployment scenarios, especially in edge, hybrid, and cloud computing environments, while acknowledging the limitations of reporting in the literature.

Table 3 presents a comparative synthesis of representative multimodal wearable health studies spanning cardiovascular monitoring, neurological intelligence, rehabilitation analytics, metabolic prediction, affective computing, and chronic disease management. Unlike Table 2, which focuses on quantitative computational benchmarking, this table emphasizes the methodological evolution, fusion strategies, deployment architectures, and clinical application domains of multimodal wearable systems.

Table 3
Comparative summary of representative multimodal wearable health studies

Study domain	Sensors	Fusion strategy	AI model	Primary application	Representative performance	Deployment architecture	Representative References
Cardiovascular monitoring	ECG, PPG	Feature-level fusion	Support Vector Machine	Arrhythmia detection	Accuracy: 92%	Edge	[24, 25, 54]
Physiological vital sign monitoring	ECG, PPG, EMG, Temperature	Data-level fusion	Random Forest	Heart rate monitoring	MAE: 3 bpm	Edge/cloud	[24, 31, 32]
Stress and behavioral analytics	EEG, HR, accelerometer	Feature-temporal fusion	CNN-LSTM	Stress detection	F1-score: 0.88	Hybrid	[29, 46, 56, 65]

(*Continued*)

Table 3
(*Continued*)

Study domain	Sensors	Fusion strategy	AI model	Primary application	Representative performance	Deployment architecture	Representative References
Metabolic risk prediction	PPG, glucose, motion	Hybrid fusion	Ensemble learning (RF + Gradient Boosting)	Hypoglycemia prediction	Sensitivity: 85%	Edge + cloud	[59, 60]
Multimodal cardiovascular and activity intelligence	ECG, motion, temperature, EMG	Multi-level fusion	Transformer-based architecture	Arrhythmia and activity recognition	Accuracy: 94%	Cloud/edge-assisted	[36, 43, 54]
Chronic disease intelligence systems	Biochemical, ECG, PPG	Self-supervised feature fusion	Contrastive SSL model	Long-term disease monitoring	AUROC: 0.91	Cloud	[46, 47, 60]
Rehabilitation and gait analytics	ECG, EMG, accelerometer	Adaptive fusion	Hybrid ML fusion	Gait analysis	Accuracy: 90%	Edge	[56, 73]
Affective computing and stress recognition	PPG, accelerometer, skin conductance	Feature-level fusion	CNN + Attention	Stress recognition	F1-score: 0.87	Edge/cloud	[2, 29]
Neurological seizure intelligence	EEG, ECG, motion, temperature	Multi-level fusion	Hybrid CNN-LSTM-Transformer	Epileptic seizure detection	Sensitivity: 92%, Specificity: 89%	Cloud	[27, 29, 55]

The reviewed studies reveal a progressive transition from classical ML approaches, such as Support Vector Machines and Random Forests, toward deep hybrid architectures incorporating CNNs, LSTMs, transformers, attention mechanisms, and SSL models. Cardiovascular monitoring remains the most mature application area due to the established reliability of ECG and PPG sensing pipelines, while neurological and behavioral monitoring increasingly depend on temporal multimodal fusion and deep representation learning for improved contextual understanding.

The table further highlights the growing adoption of hybrid edge-cloud architectures, driven by the need to balance latency, computational complexity, energy efficiency, and real-time responsiveness in wearable environments. Although advanced transformer and self-supervised models provide stronger representational capability and robustness, their higher computational demand continues to limit full edge deployment. Consequently, contemporary wearable intelligence systems are increasingly designed around adaptive and event-driven computation paradigms that strategically distribute sensing, inference, and communication tasks across edge and cloud infrastructures.

9. Conclusion

Multimodal sensing and AI-based data fusion are increasingly integral to wearable health systems to gain better physiological understanding by combining diverse biosignals like ECG, PPG, EMG, and inertial data. This review confirms that the state of the art is no longer about accuracy but stability, interpretability, and clinical feasibility of systems in practice. The main takeaway is that multimodal fusion models are prone to structural risks including sensor variability, noise, modality imbalance, and data dropout, which pose a major barrier to ambulatory use. The move to event-driven and window-based monitoring is driven by energy, thermal, and edge processing constraints, allowing for more relevant and actionable insights. Meanwhile, new paradigms, such as SSL, foundation models, and digital twin systems, herald a shift toward context-aware and adaptive physiological intelligence, albeit with their use constrained by computational and regulatory constraints. In all, the future of wearable health technologies rests on a careful balance of algorithmic complexity and system-level practicalities, moving toward robust and efficient systems that can operate for extended periods in real healthcare environments.

Recommendations for Future Research

To accelerate the development of clinically robust and scalable multimodal AI-enabled wearable health systems, the following recommendations are provided:

1) Create large-scale multi-site datasets with standardized data collection protocols to include a broad range of

demographic, physiological, and environmental factors, to enhance generalization and facilitate external validation.
2) Develop reliable cross-device calibration protocols, domain adaptation, and transfer learning approaches to deal with sensor variability and enable device interoperability.
3) Develop robust signal processing and data preprocessing methods that reduce motion artifacts, sensor drift, noise, and missing data in ambulatory settings.
4) Embrace explainable and interpretable multimodal fusion models, such as attention mechanisms, to offer clinically relevant insights and facilitate regulatory approval.
5) Emphasize energy-efficient AI through TinyML, model pruning, compression, and quantization to support robust deployment on the edge.
6) Explore closed-loop, adaptive and fail-safe systems, such as insulin delivery and neurostimulation, with a focus on safety, reliability and adherence to the regulatory process.
7) Explore stretchable, biocompatible, and multifunctional sensing platforms to enable long-term wearability, comfort, and reliable signal acquisition.
8) Perform longitudinal, real-world validation studies with robust, low-latency communication infrastructures to enable scalability, clinical relevance, and maintain system performance over time and across various populations.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Author Contribution Statement

Najeem Olawale Adelakun: Conceptualization, Methodology, Resources, Writing – original draft, Writing – review & editing, Visualization, Supervision, Project administration. **Matthew Babatunde Olajide:** Methodology, Validation, Formal analysis, Data curation, Writing – review & editing, Supervision, Project administration. **Samuel Adeniyi Omolola:** Formal analysis, Investigation, Resources, Data curation, Project administration.

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How to Cite: Adelakun, N. O., Olajide, M. B., & Omolola, S. A. (2026). Multimodal Sensing and Artificial Intelligence–Driven Data Fusion in Wearable Health Technologies, Advances, System Challenges, and Research Frontiers. *Smart Wearable Technology*. https://doi.org/10.47852/bonviewSWT62029713