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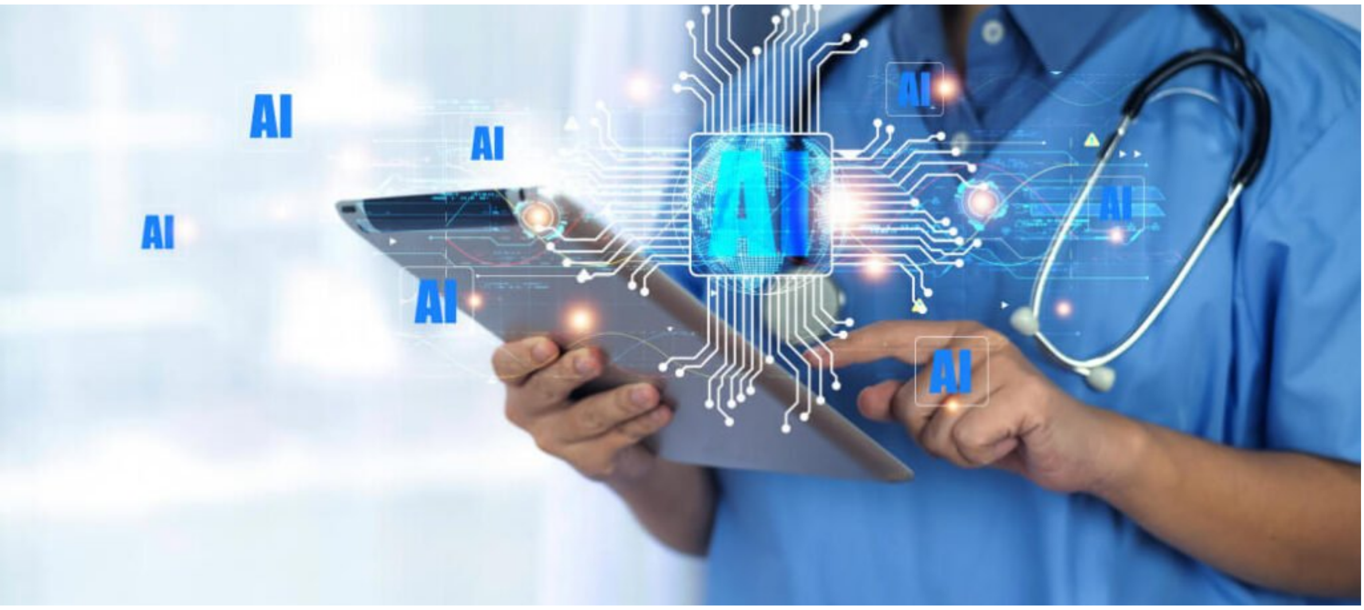


# Feasibility of ai-driven wearables for cardiac monitoring: a path toward personalized cardiac care

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**Abstract:** CVDs are the leading cause of death worldwide, accounting for approximately 17.9 million deaths annually. Management is effectively performed with continuous real-time monitoring for early detection and customized care. This paper discusses the feasibility of using AI in portable cardiac monitoring devices to overcome traditional tools such as ECGs and Holter monitors, which have always been confined to hospitals. The novelty of this work is the exploitation of AI algorithms such as machine learning and deep learning models to enhance diagnostic capabilities for wearable devices. It also presents a proposed methodology that outlines state-of-the-art wearable devices, complemented by an analysis of sensor technologies such as ECG and PPG. Real-time AI processing frameworks, including those for edge computing, are reviewed to mitigate challenges such as noisy signals or limited battery lifetimes. Ethical considerations concerning data privacy and algorithmic fairness ensure that these systems are responsibly deployed. Preliminary conclusions are that AI on wearable devices empowers cardiac care with the early detection of arrhythmias, allows for the best performance of pacemakers, and reduces hospital readmissions. This research also advances a more active strategy for integrating wearable devices with AI for the next generation in proactive and personalized cardiac care. Future work would involve the validation of those findings with clinical trials and look into broader applications in multimorbid conditions.

***Keywords:*** Cardiovascular diseases (CVDs), Artificial intelligence (AI), Wearable technology, Cardiac monitoring, Personalized healthcare

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# 1. Introduction

## 1.1. Background and Motivation

CVDs are the leading cause of death worldwide, accounting for almost 17.9 million deaths annually (WHO, 2023). Despite all the advances in medical technology, early detection and continuous monitoring still remain one of the biggest challenges of outpatient and home-based care. Early detection of cardiac abnormalities like arrhythmias, myocardial ischemia, and heart failure deterioration is of vital importance for timely intervention, reduction in hospital readmission, and improvement in patient outcomes (Lee et al., 2022).

Until today, 12-lead electrocardiograms and Holter monitors have been the most common diagnostic tests for cardiac disorders. Both are extremely limited. Hospital-based ECGs yield only snapshots of brief moments in the activity of the heart, thus usually missing transient arrhythmias or ischemic events. These monitoring systems also restrain mobility, requiring that patients visit clinical settings, and thereby render real-world tracking of cardiac function difficult. Even ambulatory solutions, such as Holter monitors, provide only intermittent monitoring, which is usually performed in spans of 24 to 48 hours. This span may be too short a time to detect less frequent cardiac abnormalities. Most such devices are bulky and uncomfortable to wear, therefore resulting in very poor patient compliance, which hinders their ability to perform as long-term monitors of cardiac patients (Kim et al., 2023).

Wearable biomedical devices bring a paradigm shift in providing continuous, non-invasive cardiac monitoring outside clinical settings. These wearable devices incorporate miniaturized biosensors that are capable of measuring electrocardiography, photoplethysmography, seismocardiography, and ballistocardiography, thus allowing real-time remote monitoring of cardiac activity without hindrance in the mobility of the patients (Kim et al., 2023). Unlike typical hospital-based systems, wearable cardiac monitors can continuously track cardiac rhythm and hence allow the identification of abnormalities well in advance and the administering of personalized health interventions.

Commercially available cardiac monitoring wearables have already shown clinical utility. The Apple Watch and Fitbit, with their PPG-based heart rate monitoring, have immense potential for the detection of AFib-a major risk factor for stroke-while AliveCor's KardiaMobile has received FDA clearance for the detection of arrhythmias using a single-lead ECG. These point to the very fact that wearable cardiac monitoring is going beyond fitness tracking into medical-grade, AI-enhanced diagnostics (Perez et al., 2019).

In essence, integration with AI and ML will further amplify the diagnosis probability of a wearable cardiac monitor. Algorithms of AI manage volumes of real-time physiological data with high precision for the identification of abnormal heart patterns. Deep learning models, including CNNs and RNNs, further empower these wearable systems in the classification of cardiac rhythms and detection of anomalies, while some are even able to predict impending cardiovascular events before their symptomatic manifestation could occur (Nguyen et al., 2024). Contrary to the traditional diagnostic techniques that rely on fixed threshold values, wearables driven by AI include a personalized approach while adapting to the individual data of patients over time.

Despite the enormous potential, there are a couple of technical challenges that AI-driven wearable cardiac monitors face in striving to ensure accuracy, efficiency, and reliability. Signal quality and motion artifacts rank among the principal challenges. As wearable sensors are naturally exposed to movement and environmental noise, there could be some kind of distortion in ECG and PPG signals, reducing diagnostic accuracy. Advanced noise-filtering algorithms and novel AI-based signal enhancement techniques are under active development, which advances real-time cardiac analysis by reducing motion-induced errors (Wu et al., 2023).

Another critical challenge for wearable cardiac monitors is to ensure computational and energy efficiency. Whereas AI-based models are computationally intensive, wearable devices have very limited processing capabilities due to their small form factor and restricted battery life. Optimized AI models developed using techniques such as TinyML, knowledge distillation, and quantization enable real-time cardiac monitoring with minimal energy consumption (Williams et al., 2023; Chen et al., 2025). New energy-harvesting technologies, such as solar-powered wearables, are also under study to enable even longer battery lifetimes and hence extended continuous monitoring capabilities (HHS, 2024).

The most important non-technical consideration for mass acceptance is the issue of privacy and security associated with AI-enabled wearables for health monitoring. Because the health of the heart concerns sensitive personal health information, the security of data and protection of privacy become extremely important. AI-powered monitoring systems have to be designed under the strict data protection regulations of HIPAA in the U.S. and the General Data Protection Regulation (GDPR) of the EU (European Commission, 2021). Federated learning is a new class of AI that enables on-device training of AI models without transferring the raw patient data to cloud servers, significantly enhancing privacy and reducing the possibility of data breaches (European Commission, 2021).

Future generations of wearable cardiac monitors powered by AI will integrate multi-modal sensor fusion, rich AI analytics, and hybrid cloud-edge computing architectures into fully automated realtime monitoring solutions. Hybrid AI models will also allow low-power, real-time inference on wearable devices, using cloud computing for more advanced predictive analytics. Other new developments also include smart pacemakers and AI-driven implantable cardiac devices for adaptive, real-time responses to cardiovascular conditions, improving cardiac disease management and patient survival rates. This wearable cardiac monitor will also be part of a smart home ecosystem in which IoT-based devices communicate to create a holistic health monitoring environment (Moshawrab et al., 2023; Dong et al., 2024).

## 1.2. Objective and scope

This study will perform a theoretical feasibility analysis of wearable cardiac monitors using AI, focusing on the following four significant aspects:

- Integration of multimodal sensors: ECG, PPG and SCG.
- Computational feasibility with respect to real-time AI processing.
- Energy efficiency in relation to energy consumption constraints.

This is not an experimental study; no prototype has been developed and no clinical trials have been carried out. However, the various technological and practical obstacles that exist in deploying an AI-powered cardiac monitoring system are considered.

# 2. Feasibility of Wearable Sensor Technologies

Wearable cardiac monitoring devices generally use different sensor technologies, which provide the actual acquisition of physiological and biomechanical signals. In fact, each type of sensor technology has advantages facing many challenges, including those dealing with accuracy and power consumption, while ensuring efficiency during processing. In essence, their usage ideally should ensure low energy consumption while guaranteeing high signal fidelity even at extreme intensities of motion, which would be expected from reliable cardiac monitoring.

## 2.1. Electrocardiography (ECG)

The ECG is still considered the gold standard for monitoring arrhythmias, heart rate variability, and myocardial ischemia. The ECG sensors measure the electrical activity of the heart through electrodes attached to the skin that record changes in voltage as the heart contracts and relaxes.

Benefits will be ECG that will be highly diagnostic, with great accuracy in detecting arrhythmias, clinical validation in both hospital and portable applications, and the real-time, continuous monitoring of patients in acute situations. PECG usual challenges include motion artefacts, which make signals less reliable in portable format; it requires a bigger power supply for continuous operations and electrode placement affects signal quality.

Recent development of flexible ECG sensors dramatically improves the quality of signal acquisition, reducing noise introduced by subject movement and allowing higher portability. The implementation of new dry electrode technologies free from conductive gel is yet another effort aimed at improving the patient’s comfort, thus extending the portability time (Kim et al., 2023).

## 2.2. Photoplethysmography (PPG)

Because this technology is by definition non-invasive and low power, it finds many applications in consumer smart wearables and fitness trackers. Light sources within PPG sensors produce infrared or green light, the absorption of which changes with each heartbeat, reflecting changes in blood volume.

Advantages of PPG are that it consumes low power and is thus fit for battery-powered wearables. It is also non-invasive, with no need to touch skin directly, unlike the electrodes in ECG. The small size and low cost hence make it very applicable in many commercial wearable devices.

However, some challenges still exist : It is prone to motion artefacts and noise, hence its accuracy can degrade. Low HRV accuracy results in a non-reliable diagnosis. Poor performances on subjects with darker skin brings up a bunch of bias related issues.

Regarding the enhancement in PPG, AI-based de-noising algorithms and multi-wavelength techniques in literature put in place by different researchers compensate for variations in skin tone and motion artefacts compensation (Wu et al., 2023).

## 2.3. Seismocardiography (SCG) and ballistocardiography (BCG)

There are two presently used methods to measure cardiac mechanical activity: Seismocardiography and ballistocardiography. Both these methods offer more additional information on cardiac performance that cannot be provided by either ECG or PPG.

SCG records chest wall vibrations produced by myocardial contractions. It gives information about contractility and the ejection fraction of the cardiac cycle.

It provides the identification of micro-vibrations in the body resulting from cardiac output and ejection of blood into the circulation. So many advantages, but just to name a few: SCG and BCG have better overall system reliability by complementation with ECG and PPG. They offer a noninvasive way to estimate cardiac contractility. They can also be incorporated into wearable patches or smart clothes.

Their major drawbacks are as follows: Sensor placement is critical with regard to the accuracy of the results. SCG-BCG signals are of relatively low resolution compared to ECG methods. Signal interpretation is very resource-consuming, considering computational resources.

Despite all these issues, SCG-BCG fusion with AI-based multimodal cardiac monitoring becomes a promising direction of research (Moshawrab et al., 2023; Dong et al., 2024).

## 2.4. Multimodal sensor fusion

In this context, the ECG, PPG and SCG offer multimodal integration of the sensor fusion for multifold enhancement in the reliability and precision of these three sensors. Besides that, the multi-sensor technique so devised reduces each kind of individual inconvenience while providing a very powerful cardiac anomaly investigation system.

Example: the ECG is very accurate for monitoring the electrical activity of the heart, while being very sensitive to the movement artefact itself; on the other hand, the PPG is not very powerful and is easy to wear, but its diagnostic value is low in terms of heart rate analysis; while the SCG provides mechanical information and improves the analysis of contractility.

However, multimodal integration leads to computational complexity and power requirements, which calls for hardware and software architectures optimised for real-time processing (Zhou et al., 2023; John et al., 2024). Edge computing and AI-enhanced signal processing solutions are being developed to address these challenges.

The following chart compares ECG, PPG and SCG in terms of accuracy, energy efficiency and robustness to motion to provide a better comparison of the strengths and weaknesses of each sensor type.

**Figure 1.** Comparison of Wearable Cardiac Sensor Technologies

This figure represents the fact that there is a trade-off in the sensor types, and the optimum needs to hybridize them into a balancing act among accuracy, power consumption, and robustness toward motion artifacts. While ECG has excellent diagnostic precision, it is power-consuming and sensitive to motion. PPG is energy-efficient but lacks real-world accuracy. SCG is useful for mechanical insight but involves precise sensor placement.

Wearable cardiac monitors can achieve maximum reliability and diagnostic performance using multi-modal sensor fusion in the face of a variety of individual sensor limitations. The forthcoming next generation of wearable AI-enabled personalized health will be integrated.

# 3. AI-Based Signal Processing in Cardiac

# Monitoring

The development of AI-driven wearables for cardiac monitoring should go hand in hand with sophisticated signal processing techniques to provide real-time, precise detection of anomalies in the heart, which in turn would mean a balance between energy efficiency and computational constraints. Traditional cloud-based processing introduces latency, raises privacy concerns, and dependency on network connectivity. In its place, edge AI has started to emerge as the favored choice where ondevice AI inference will result in faster and more secure diagnosis without transferring sensitive data to external servers.

It is challenging to realize this in light of memory, computational power, and energy requirements imposed by deep learning models. Wearables with suitable architecture in AI together with techniques of model optimization will meet the challenges of high diagnostic accuracy at power constraints.

## 3.1. Wearable AI Architectures

Therefore, sophisticated techniques in signal processing have developed to become an integral ingredient of trade-offs involving energy efficiency, computation constraints, and real-time anomaly detection of the heart. Most of all, it was limited by latency and issues related to data privacy, given that cloud-based processing is highly dependent on connectivity. Edge AI has hence grown as one of the preferable ways where inference of on-device AI may speed up and thus secure the diagnoses without needing the transmission of sensitive information to servers sitting at distant locations.

Deep learning models, with huge demands in memory, computational power, and energy, cannot be directly deployed on wearable devices. Efficient AI architectures and model optimization techniques have been employed for making a wearable device operate under power constraints with high diagnostic accuracy (Nguyen et al., 2024).

***Convolutional Neural Networks for ECG Classification***

The wide applications of CNNs in ECG waveform classification include proficiency in extracting spatial patterns and detecting abnormalities such as AFib, ventricular tachycardia, and bradycardia. Several CNN-based models, trained on vast amounts of ECG datasets, were then deployed into FDAapproved wearable devices owing to their high diagnostic precisions (Nguyen et al., 2024).

CNN benefits in ECG classification: High accuracy of detection of cardiac abnormalities, feature extraction is automatic, with not much manual analysis required. Suitable for real-world wearable deployment.

Challenges with CNN: Though possible, some reduction of the computational load can be achieved through optimization.

***Hybrid CNN-LSTM Model for Time-Series Analysis***

Although performing well, CNNs cannot catch long-run temporal dependencies in cardiac signals. Hence, RNN variant-LSTM-comes out to be ideal for applications dealing with such sequential timeseries data. Therefore, the study of heart rate variability and anomaly detection within become of extensive usage. The hybrid model employs a combination of both: CNN for feature extraction from the ECG waveform and LSTM for analyzing the time-dependent trends in HRV.

It benefits from this hybrid model in enhancing AI-based cardiac monitoring, especially for diagnosis related to heart failure, ischemia, and the progression of arrhythmias (Nguyen et al., 2024). ***Model Optimization on Wearable Devices***

Deep learning models, although very memory-intensive and computationally expensive, need optimization on these resource-constrained wearable devices. The major techniques include:

- Knowledge Distillation: The technique of knowledge transfer from a big, complex AI model into a small, efficient one reduces computational demand.
- Quantization: A good example is reducing 32-bit floating-point models to 8-bit integer models, which decreases memory usage by 75% while maintaining accuracy (Nguyen et al., 2024).
- Pruning: This removes unnecessary neural connections, hence decreasing model complexity without major loss in accuracy.

It could be inferred that all these methods of optimization will allow efficiency in ECG signal processing with battery life in AI-powered wearables while ensuring high diagnostic performance.

**Figure 2.** AI Processing In Wearable Cardiac Monitoring

The following is a summary of the flowchart above for the sequential AI processing pipeline in wearable cardiac monitoring systems:

1. Wearable sensors comprising ECG, PPG, and SCG capture physiological signals.
2. Pre-processing operations filter noise from the signal and normalize it, hence preparing it for superior processing by the artificial intelligence system.
3. Feature extraction that would, in turn, bring out some critical waveform patterns.
4. The CNN-based classifiers classify the signals of ECG and detect any arrhythmia.
5. LSTM analyzes temporal variations of heart rate variability.
6. A hybrid CNN-LSTM model fuses spatial and temporal features for accurate anomaly detection.
7. When an anomaly is detected, diagnostic alerts are triggered, hence allowing for real-time
8. Feedback is provided instantly to the user via a smartphone or wearable interface.

This AI-based approach provides fast real-time cardiac monitoring, improving early diagnosis, patient engagement, and personalized healthcare.

## 3.2. Federated Learning for Preserving Privacy

One huge challenge in AI-powered monitoring is how to assure data privacy for the patient. Traditional cloud AI involves continuous data uploading, raising several regulatory and data ownership issues apart from other security concerns. Thus, the newly developed architecture, known as federated learning, enables model training on devices where patients maintain their private data (Williams et al., 2023).

How Federated Learning Works:

1. Each wearable device trains an AI model locally with patient-specific ECG and PPG data.
2. Instead of raw data transmission to the central server, model updates are transmitted.
3. The global AI model, on a central server, is refined by aggregating updates from multiple
4. Return the improved AI model from wearables in order to boost the accuracy while not

exposing any patient data (Williams et al., 2023).

Some key takeaways the principals can have from Federated Learning in wearables are: Data privacy is guaranteed since no raw patient data is being sent out. It reduces bandwidth and power consumption, hence more efficient. Learns from decentralized data sources increasing model accuracy across diverse populations. Complies with regulations (HIPAA, GDPR) and thus enables ethical AI deployment (HHS, 2024), (European Commission, 2021).

**Figure 3.** Federated Learning In Wearable Cardiac Monitoring

The above flowchart represents how FL works in wearable cardiac AI systems:

1. Wearable devices themselves, like smartwatches and ECG patches, locally train an AI model based on patient-specific ECG and PPG data.
2. Instead of sharing raw data, encrypted model updates are sent to a central AI server.
3. The central server aggregates updates arriving from multiple devices, refining the global AI model.
4. The improved global model is broadcast to the participating devices in order to improve the local AI models further.
5. Every device keeps on training on freshly added data and, in parallel, continuously improving onboard AI performance.

What this means is that there is no leakage of information outside the device; hence, security and compliance are inherently improved, further optimizing AI diagnostics.

Cardiac monitoring by next-generation wearables will be entirely dependent on AI-enabled signal processing. Hybrid CNN-LSTM architecture, on-device model optimizations, and even privacypatient data-based federated learning are the powerful building blocks to drive AI forward in wearables. That would open up pathways to real-time, personalized, proactive cardiac care.

# 4. Power Consumption and Energy Efficiency in AI-Driven Wearable Cardiac Monitoring

Continuous operation of AI-driven wearable cardiac monitors requires minimal power consumption to ensure long battery life and continuous monitoring. As wearable devices use small rechargeable batteries, it is essential to reduce power consumption so that they can be used in the real world (Gautam et al., 2022; Zheng et al., 2025).

## 4.1. Power Consumption Analysis

The total power consumption of an AI-driven wearable cardiac monitoring system is influenced by three primary components:

**Table 1.** Power Consumption Analysis of AI-Driven Wearable Cardiac Monitoring Components

- ECG sensor: 2.1 mW. ECG electrodes require continuous acquisition of the electrical signal that is part of the baseline consumption.
- MCU running AI inference: 3.2 mW. AI-driven classification and HRV analysis require heavy computation; hence, this module is one of the highest power-consuming components.
- BLE transmission: 1.5 mW. Wireless communication is required for real-time monitoring; however, BLE data transmission still remains power-consuming.

Although 6.8 mW is a small value, considering long-term operation, a regular battery, for example, 40 mAh Li-Po, will be quickly depleted if no energy optimization strategies are implemented (Gautam et al., 2022; Zheng et al., 2025).

## 4.2. Energy Efficiency Optimization Strategies

To extend the battery life and make AI-powered wearables more sustainable, several optimization techniques are employed:

# a.Power Reduction by Duty Cycling

Instead of continuous operation, sensors can be turned on periodically to avoid unnecessary power consumption.

ECG sensors can sample in intervals, such as every 5 seconds, rather than constantly, which already can cut energy consumption by as much as 40%.

Event-triggered monitoring: AI may detect irregular cardiac patterns before the full monitoring mode is turned on, further extending battery life.

# b.TinyML for Efficient AI

- Tiny Machine Learning-TinyML-allows low-power AI processing directly on the MCU.
- Model quantization and knowledge distillation shrink AI model size by 75%, enabling

more powerefficient real-time inference.
- Optimized neural network architectures, for example, MobileNet or Edge TPU models, reduce the computational overhead with no loss in accuracy.

# c.Energy Harvesting for Self-Powered Wearables

- Wearable patches or smartwatches can be integrated with flexible photovoltaic cells. The cells yield up to 10 µW/cm² under indoor lighting conditions, increasing battery lifetime by 20%. • Energy-harvesting TEGs are able to convert body heat into electrical energy continuously for supplementing power (Gautam et al., 2022; Zheng et al., 2025)

**Figure 4.** Power Optimization In Wearable AI Monitoring

The key power optimization techniques will enable a single charge to keep an AI-driven cardiac monitor running for much longer and thereby make it a more viable activity in practical medical applications.

Above is the flowchart that demonstrates how an AI-driven wearable cardiac monitor saves power:

1. AI-Driven Wearable Cardiac Monitoring: High, 6.8 mW, because the sensors operate constantly, along with AI inference and BLE transmission.
2. Application of optimization techniques leads to energy efficiency.
3. The following are three major power-saving techniques implemented:

- Duty Cycling: The activation of sensors is reduced, thus minimizing the wastage of energy on redundant usage.
- TinyML optimisation: This enables AI inference with low energy consumption, reducing the computational load.
- Energy harvesting: Energy production based on solar and body heat increases battery life.

These methods, once implemented, materialize a wearable device with optimized, extended battery life that may allow real-world wearability.

Power consumption analysis identifies ECG sensors, AI interference, and BLE transmission as major power-consuming components. With different optimization strategies in place, such as Duty Cycling, TinyML, and Energy Harvesting, it helps reduce the power usage in order to extend battery life. How energy efficiency can be achieved in AI-driven wearables.

# 5. Feasibility Analysis of AI-driven Wearable Cardiac Monitoring

Overall, the viability of AI-driven wearable heart monitors will be driven by sensor accuracy, processing capability, energy efficiency, connectivity, user experience and regulatory compliance. Although considerable progress has been made in AI-based signal processing, a number of technical, practical and regulatory challenges need to be addressed before widespread diffusion can take place. (Moshawrab et al., 2023; Dong et al., 2024).

This section considers each important component of the AI-powered wearable cardiac monitoring system in depth to analyze its advantages, challenges, and feasibility ratings in view of the current stage of development and their future potentials. Feasibility ratings □ out of 5 are given to denote how ready a component is for deployment and also to show areas where further optimizations are needed.

The following feasibility breakdown will analyze respective strong points, some limitations, and technological gaps in the implementation of wearables with enhanced AI cardiac monitoring.

# Feasibility Breakdown

**Table 2.** Feasibility Assessment of AI-Driven Wearable Cardiac Monitoring Components

This feasibility assessment highlights the current readiness and limitations of each component of AIdriven cardiac wearable devices. While there have been significant advances in the core technologies of wearable sensors, AI-based signal processing and wireless communication, privacy, regulatory compliance and energy efficiency remain areas that require improvement to enable scalability for real-world adoption.

# 6.Conclusion

This work justifies the technical feasibility of integrating multimodal sensors with edge AI processing and AI-driven wearable cardiac monitoring based on the principle of federated learning. Advanced biosensors, real-time AI algorithms, and low-power processing techniques finally meet to bring about continuous, personalized cardiac monitoring with enhanced diagnostic accuracy, the possibility of early detection of arrhythmias, and proactive intervention strategies. In this way, the final results of the research will be minimized re-admission to hospitals, improved patient outcomes, and an important step toward remote healthcare.

However, besides these technological developments, several important challenges have to be resolved before this technology could see general clinical applications, which include:

- Sensor reliability
- Energy efficiency
- Wireless communication & data security
- Regulatory and ethical considerations

Wearable devices for cardiac monitoring using AI have the immense capability to bring in a paradigm change in personalized cardiac care. This AI-powered wearable device will connect powerfully amongst technology, medicine, and regulatory frameworks to make proactive cardiovascular disease management a possibility from mere diagnosis-based treatment to continuous home-based monitoring. Simultaneously, it empowers patients, reduces the healthcare burden, and hence improves overall cardiac health outcomes in the world.

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