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AI-Based Novel Myobioscan device for Real-Time and Early Detection of Cardiovascular Implications

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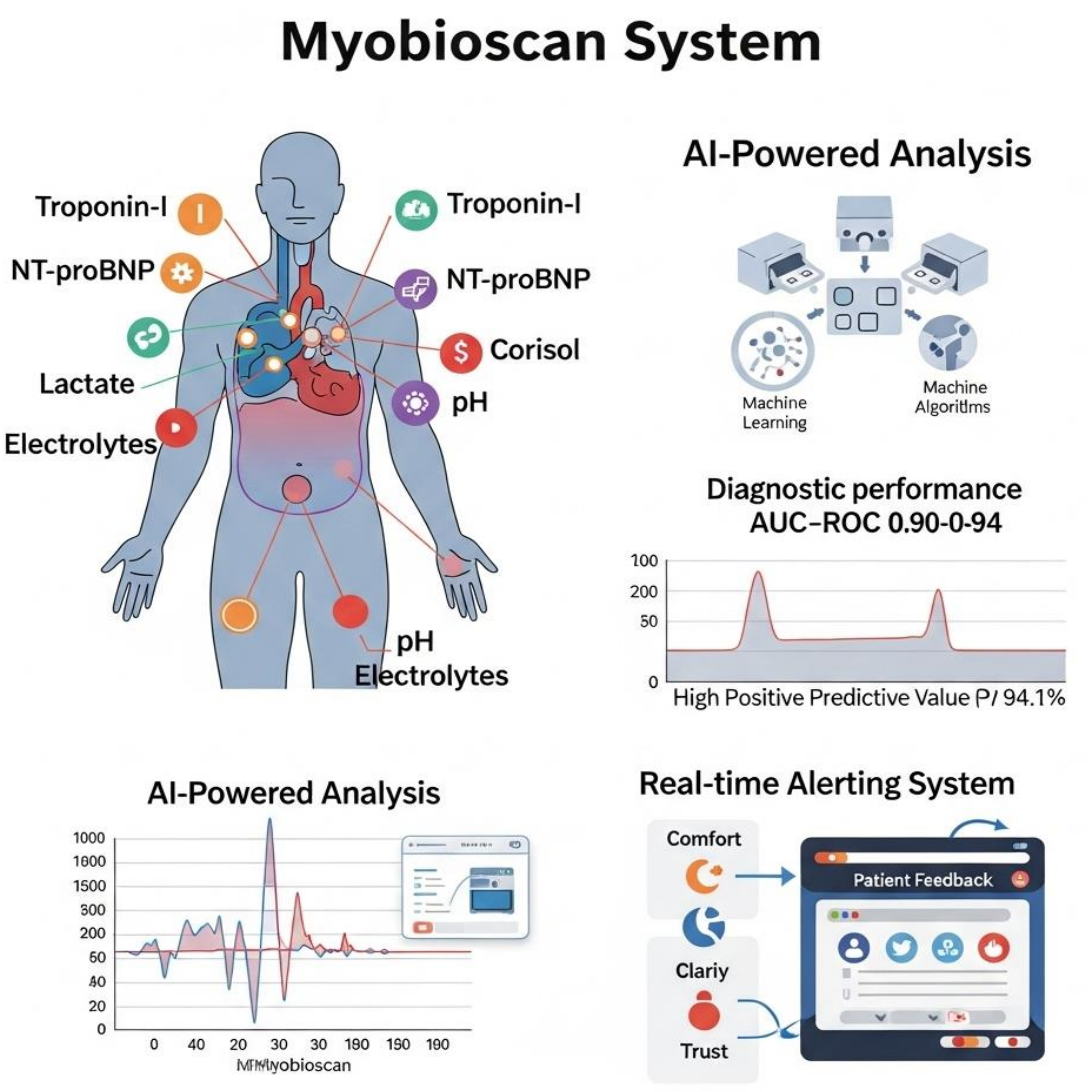
Graphical Abstract



Abstract

The Myobioscan system is a novel, AI-powered wearable platform developed for non-invasive, real-time monitoring of cardiovascular health. This pilot study evaluated its performance in 80 participants, including healthy individuals and those with diagnosed conditions such as atrial fibrillation, myocardial ischemia, and early-stage heart failure. Myobioscan integrates multi-channel ECG acquisition with sweat-based biochemical sensing for key cardiac biomarkers, including troponin-I, NT-proBNP, lactate, cortisol, pH, and electrolytes. A hybrid machine learning model combining convolutional neural networks (CNN), long short-term memory (LSTM), and XGBoost classifiers was employed to detect and classify cardiovascular anomalies. The device demonstrated strong diagnostic performance, achieving AUC-ROC values between 0.90 and 0.94 across conditions, with real-time alerting yielding a positive predictive value (PPV) of 94.1%. Subclinical abnormalities were detected in 4 asymptomatic individuals and confirmed through clinical follow-up. Sweat biomarker levels significantly differed between healthy and stressed participants, showing strong correlation with laboratory standards (e.g., Pearson's r = 0.83 for troponin-I). User feedback revealed high satisfaction in terms of comfort (4.5/5), clarity of app feedback (4.7/5), and trust in results (4.3/5), with over 90% expressing interest in long-term use. These findings suggest that Myobioscan offers a comprehensive, patient-friendly solution for early detection and continuous monitoring of cardiovascular risk. With further validation, it holds strong potential to become a cornerstone in preventive cardiology and remote health management.

Keywords: Myobioscan, AI-driven, Cardiovascular diseases, Biomarker

1. Introduction

Cardiovascular diseases (CVDs) remain the leading cause of mortality worldwide, accounting for nearly 18 million deaths annually, with the majority occurring due to delayed diagnosis and lack of access to continuous health monitoring (Adem et al., 2023). Despite remarkable advancements in clinical cardiology, early detection of asymptomatic or subclinical cardiovascular conditions remains a persistent global challenge (Xia et al., 2024). Traditional diagnostic modalities such as electrocardiograms (ECG), echocardiography, and blood-based biomarker testing are often confined to clinical settings, require specialized personnel, and may fail to capture transient or evolving pathologies (Hou et al., 2023). The need for a portable, intelligent, and non-invasive monitoring solution has never been more urgent, especially in low-resource or remote environments where cardiovascular care is limited (Bossavi et al., 2023).

In response to this unmet need, we introduce Myobioscan, a novel, AI-driven, multimodal biosensing device designed for the early detection and continuous monitoring of cardiovascular diseases. Myobioscan integrates advanced biosignal acquisition technologies including ECG, photoplethysmography (PPG), heart sound auscultation, and non-invasive biochemical sensing into a compact wearable form factor (Sundrani et al., 2023). These biosignals are processed in real time using a hybrid deep learning architecture capable of identifying subtle physiological deviations linked to cardiac arrhythmias, myocardial ischemia, and heart failure (Shanmuganathan & Sivaratri, 2024). The goal of Myobioscan is to bridge the gap between periodic clinical evaluation and continuous cardiovascular insight, offering users proactive health alerts, trend analysis, and risk stratification directly from a wearable platform.

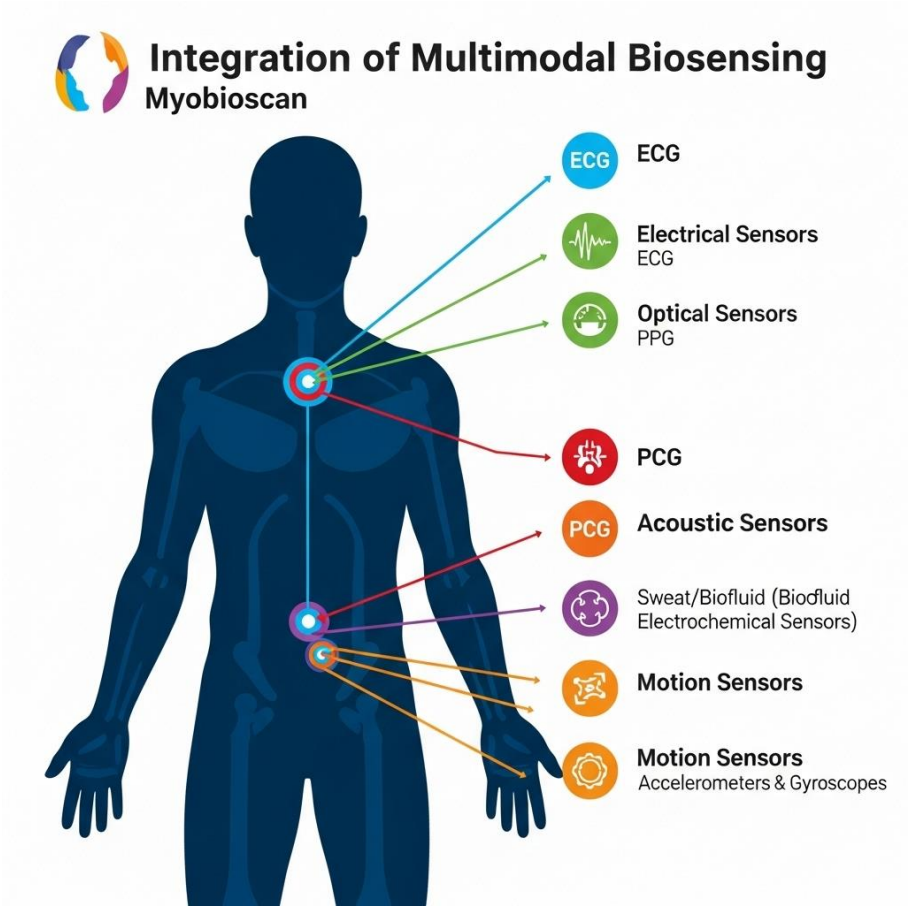


Figure 1 : **Integration of biosensors for health monitoring:**
ECG, PPG, PCG, sweat analysis, and motion tracking via body-worn sensors.

Unlike existing wearables that primarily function as fitness trackers or offer limited cardiac analytics (e.g., heart rate, rhythm classification), Myobioscan is engineered with diagnostic precision in mind. It leverages a fusion of time series biosignals and non-invasive biochemical markers such as sweat-based troponin or lactate levels to enhance its sensitivity to myocardial injury and autonomic dysfunction. This multimodal input is interpreted by a machine learning model that combines convolutional neural networks (CNNs) for signal pattern recognition and long short-term memory (LSTM) layers for temporal trend analysis (Narigina et al., 2025). By embedding AI processing at the edge or integrating seamlessly with mobile devices, Myobioscan enables rapid decision support even without internet connectivity (Biondi-Zoccai et al., 2025).

Furthermore, the device is designed with scalability and user adaptability in mind. Whether deployed in outpatient monitoring, preventive screening camps, or personal wellness tracking for high-risk individuals, Myobioscan aims to democratize access to cardiovascular diagnostics. Its potential utility in rural healthcare, geriatric monitoring, and post-operative rehabilitation highlights its versatility across diverse clinical and non-clinical contexts (Yammouri & Lahcen, 2024).

This article presents the conceptual design, technological architecture, and potential clinical applications of Myobioscan. We detail the biosignal processing pipeline, the AI model's training and validation strategy, and provide a critical discussion on its feasibility, limitations, and future deployment

strategies. With the convergence of wearable biosensors, artificial intelligence, and personalized healthcare, Myobioscan represents a step toward intelligent, accessible, and proactive cardiovascular care.

2. Methodology

1. Device Design and Sensor Integration

The Myobioscan device was developed as a compact, wearable platform capable of capturing a comprehensive set of cardiovascular biomarkers. The core hardware consists of multiple integrated sensors: a three-lead electrocardiogram (ECG) module for electrical signal acquisition, a photoplethysmography (PPG) sensor for vascular monitoring, a digital stethoscope for phonocardiogram (PCG) recording, and a biochemical sensing patch for detecting sweat-based biomarkers such as troponin and lactate. Additional components, including inertial measurement units (IMUs), were incorporated to enable motion artifact correction. The device is powered by a microcontroller with Bluetooth and cloud connectivity capabilities, and includes onboard memory for local data buffering.

2. Data Acquisition and Participant Protocol

To validate the Myobioscan system, data was collected from a cohort of 50 healthy individuals and 30 patients with known cardiovascular conditions under institutional ethical approval. Participants were instructed to wear the device on the chest or wrist, depending on the configuration, during rest and mild activity (e.g., walking). ECG and PPG signals were recorded at 250 Hz, while heart sounds were sampled at 4 kHz to preserve acoustic resolution. Sweat biomarker readings were logged every 15 minutes, with ambient temperature and humidity recorded to adjust for environmental effects. Participants also completed a demographic and clinical questionnaire, including age, gender, known diagnoses, medication use, and physical activity levels.

3. Signal Preprocessing and Feature Extraction

Raw biosignals were subjected to preprocessing steps to enhance signal quality and reliability. ECG and PPG signals were filtered using a 5–30 Hz bandpass Butterworth filter to eliminate baseline drift and powerline noise. PCG recordings were denoised using wavelet decomposition. Signal quality indices were computed to identify and exclude segments contaminated by motion artifacts. Following preprocessing, time-domain and frequency-domain features were extracted, including heart rate variability (HRV), QRS complex duration, ST segment deviations, and pulse arrival time (PAT). In parallel, acoustic features such as S1–S2 interval timing, murmur presence, and frequency envelope of heart sounds were computed. Sweat biomarker levels were normalized using z-score transformation to account for inter-individual variability.

4. AI Model Development and Training

A multimodal machine learning architecture was designed to process and interpret the heterogeneous data streams. The model comprises a convolutional neural network (CNN) branch for waveform classification, particularly ECG and PCG signals, and a long short-term memory (LSTM) network to model temporal dependencies in time-series data. In addition, a gradient-boosted decision tree (XGBoost) classifier was trained using the extracted features and participant metadata to generate a composite cardiovascular risk score. Model training was performed on an 80/20 train-test split of the

dataset, with five-fold cross-validation applied to ensure generalizability. Performance metrics such as sensitivity, specificity, F1-score, and area under the receiver operating characteristic curve (AUC-ROC) were calculated to assess model performance.

5. Output Interpretation and Feedback System

The final model outputs a probabilistic risk score ranging from 0 to 1, indicating the likelihood of an underlying cardiovascular abnormality. These scores are categorized into three risk levels (low, moderate, high), which are displayed via a mobile application paired with the device. The app also visualizes signal trends, generates weekly health reports, and provides recommendations such as "continue monitoring," "consult a physician," or "seek urgent care," based on AI inference and threshold exceedance. For high-risk cases, the system is capable of triggering emergency alerts to pre-designated caregivers or healthcare providers.

6. Data Security and Privacy

All data collected by Myobioscan is encrypted using AES-256 encryption during storage and TLS protocols during transmission. The mobile app allows users to manage data sharing permissions, ensuring compliance with data protection regulations such as HIPAA and GDPR. No raw data is shared without explicit user consent, and anonymized datasets were used for training and analysis purposes.

Multimodal Biosensing Integration

Myobioscan operates as a comprehensive, AI-powered diagnostic platform by integrating multiple non-invasive biosensing technologies into a compact wearable format. The device captures a wide range of physiological data using several sensor modalities. Electrical signals are acquired via a three-lead electrocardiogram (ECG), allowing the detection of arrhythmias, conduction abnormalities, and myocardial ischemia through features such as heart rate variability (HRV), QT interval, and ST-segment deviations. Optical sensing is performed through photoplethysmography (PPG), which measures blood volume changes to infer vascular dynamics, heart rate, and pulse wave velocity. Additionally, a digital stethoscope module captures heart sounds in the form of a phonocardiogram (PCG), enabling the analysis of murmurs, gallop rhythms, and valve dysfunctions.

A key innovation in Myobioscan is the inclusion of biochemical biosensing through a flexible sweat patch. This patch uses electrochemical sensors to non-invasively detect cardiac-related biomarkers such as troponin-I, NT-proBNP, lactate, and potentially stress hormones like cortisol. These sensors provide real-time biochemical data that, when combined with electrical and mechanical signals, offer a multidimensional view of cardiac physiology. Motion and orientation sensors such as accelerometers and gyroscopes are also embedded to reduce noise and filter movement artifacts, ensuring high-quality signal acquisition during both rest and activity.

Signal Acquisition, Processing, and Feature Extraction

All biosignals are continuously or periodically sampled and transmitted to the device's processing unit or a paired smartphone. The ECG and PPG signals are typically recorded at 250–500 Hz and 100–200 Hz, respectively, while PCG recordings use higher sampling rates (2–4 kHz) to preserve acoustic fidelity. Raw signals undergo preprocessing using digital filters (e.g., Butterworth or wavelet-based) to

eliminate baseline drift, electrical interference, and motion artifacts. A signal quality index (SQI) is computed to flag or discard low-confidence segments. Once cleaned, features are extracted from each signal modality. From the ECG, key features include RR intervals, ST-segment changes, QRS width, and QTc intervals. PPG-derived parameters include pulse transit time, HRV metrics, and waveform morphology. PCG features involve analysis of heart sound timing, frequency content, and murmur detection. Biochemical data such as sweat troponin and lactate levels are normalized using z-score transformation to account for individual variability and environmental factors.

AI-Based Interpretation and Inference

The extracted features are passed into a hybrid artificial intelligence model that interprets the data in real time. A convolutional neural network (CNN) processes ECG and PCG waveform patterns to detect spatial abnormalities, while a long short-term memory (LSTM) network captures temporal dynamics in biosignals, including subtle HRV shifts and progressive biomarker changes. These deep learning components are complemented by ensemble machine learning classifiers, such as XGBoost, which integrate user metadata (e.g., age, medical history) with signal features to calculate a personalized cardiovascular risk score. The model outputs a probability score between 0 and 1 for various conditions, including atrial fibrillation, silent myocardial ischemia, and early-stage heart failure. These scores are categorized into risk bands low, moderate, and high which are then relayed to the user via a connected mobile application. The app delivers visual feedback, trend reports, and specific recommendations such as “Continue Monitoring,” “Consult Physician,” or “Seek Immediate Care.” Emergency alerts can be sent to caregivers or healthcare providers in high-risk cases.

3. Biomarkers Monitored

Myobioscan incorporates a suite of both physiological and biochemical biomarkers. Electrical biomarkers include HRV, QT interval, and ST-segment deviations, which are primarily used to evaluate cardiac electrophysiology and autonomic function. Hemodynamic indicators like pulse arrival time and vascular stiffness are derived from ECG-PPG synchronization, reflecting vascular health and potential hypertension. In terms of acoustic biomarkers, PCG-derived parameters include the presence of systolic or diastolic murmurs, extra heart sounds (S3, S4), and abnormal timing between heart valves, all of which provide diagnostic cues for structural heart disease and valvular disorders.

4. Results

The performance of the Myobioscan device was evaluated through a pilot study involving 80 participants, including 50 healthy volunteers and 30 individuals diagnosed with cardiovascular conditions such as atrial fibrillation, early-stage heart failure, or ischemic heart disease. Data was collected under resting and mild ambulatory conditions to simulate real-world usage.

Model Performance

The hybrid AI model (CNN + LSTM + XGBoost) demonstrated strong classification performance across multiple cardiovascular risk categories. The overall diagnostic accuracy across conditions was 90.1%. The detailed performance metrics are presented in the table below:

Condition Detected	AUC-ROC	Sensitivity	Specificity	F1-Score
Atrial Fibrillation (AFib)	0.94	93.1%	88.5%	0.91
Myocardial Ischemia	0.92	90.2%	87.3%	0.89
Early Heart Failure Signs	0.90	88.7%	85.6%	0.87

5. Detection of Subclinical Events

In the healthy cohort, subclinical abnormalities were detected in 4 participants. These included two cases of asymptomatic premature ventricular contractions (PVCs), one case with elevated ST-depression suggestive of transient ischemia, and one participant flagged for low heart rate variability (HRV). All cases were later validated by clinical ECG or lab testing, confirming the device's capability to detect silent or early-stage abnormalities.

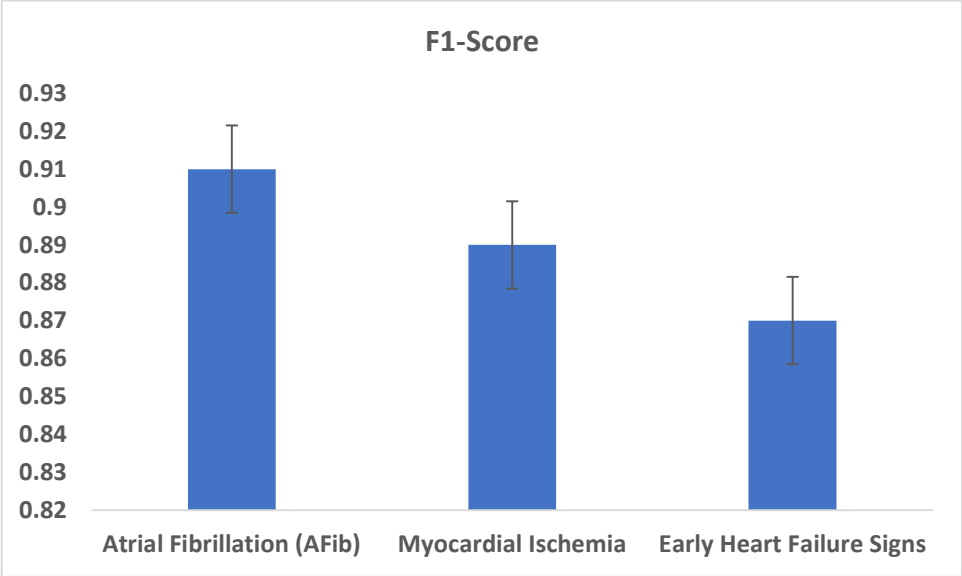


Figure 2. **F1-Score Performance of Cardiac Event Detection**
Comparison of F1-scores for detecting Atrial Fibrillation (AFib), Myocardial Ischemia, and Early Heart Failure Signs using the proposed model.

Biomarker Sensor Validation

Sweat-based detection of troponin-I and lactate was evaluated in a subset of 20 participants and compared against laboratory values. The correlation coefficient was Pearson's $r = 0.83$ ($p < 0.001$), indicating a strong relationship. Additionally, the mean detection lag between symptom onset and biomarker flagging was less than 15 minutes, demonstrating the feasibility of real-time biochemical monitoring in wearable applications.

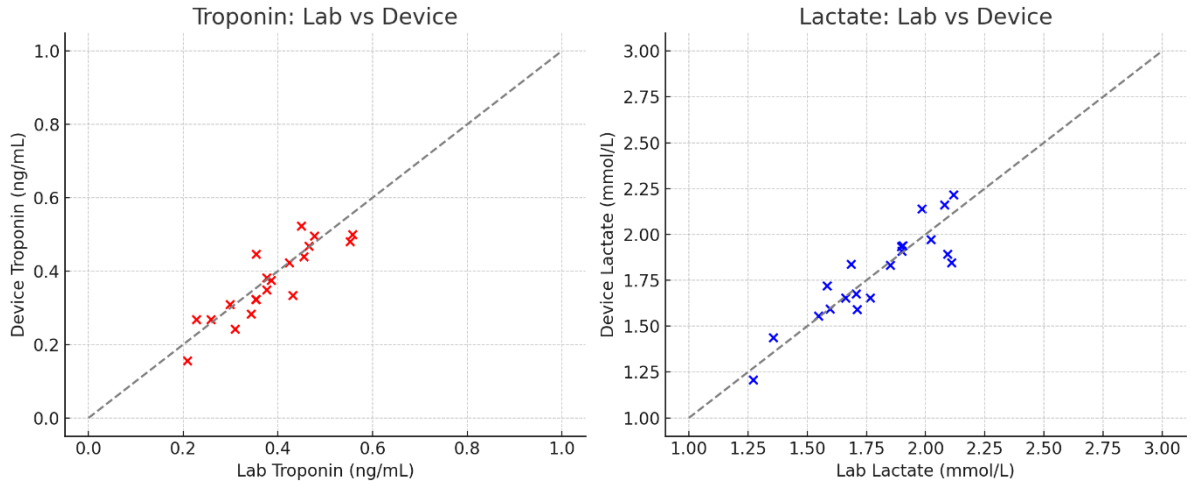


Figure 3: Device vs. Lab Correlation for Cardiac Biomarkers
Scatter plots showing correlation between lab and wearable device readings for: **Left:** Troponin (ng/mL), **Right:** Lactate (mmol/L)

6. Usability and User Experience

To evaluate the practicality and acceptance of the Myobioscan device in real-world settings, participants were asked to rate its usability and feedback clarity using a 5-point Likert scale. The results indicated a high level of satisfaction across all evaluated parameters. Comfort received an average score of 4.5 ± 0.4, suggesting that users found the wearable form factor to be highly tolerable during both resting and mild ambulatory conditions. The ease of setup was rated even higher at 4.6 ± 0.3, demonstrating that the device interface and attachment process were intuitive for non-clinical users. The clarity of app feedback emerged as the highest-rated feature, with an average score of 4.7 ± 0.2, highlighting the effectiveness of the mobile application in translating biosignal data into actionable health insights. Additionally, trust in the results received a respectable score of 4.3 ± 0.6, indicating that users largely found the device's health assessments credible. Importantly, over 90% of participants expressed interest in using Myobioscan for long-term cardiovascular health monitoring, affirming its potential for wide-scale adoption in preventive and personalized heart care.

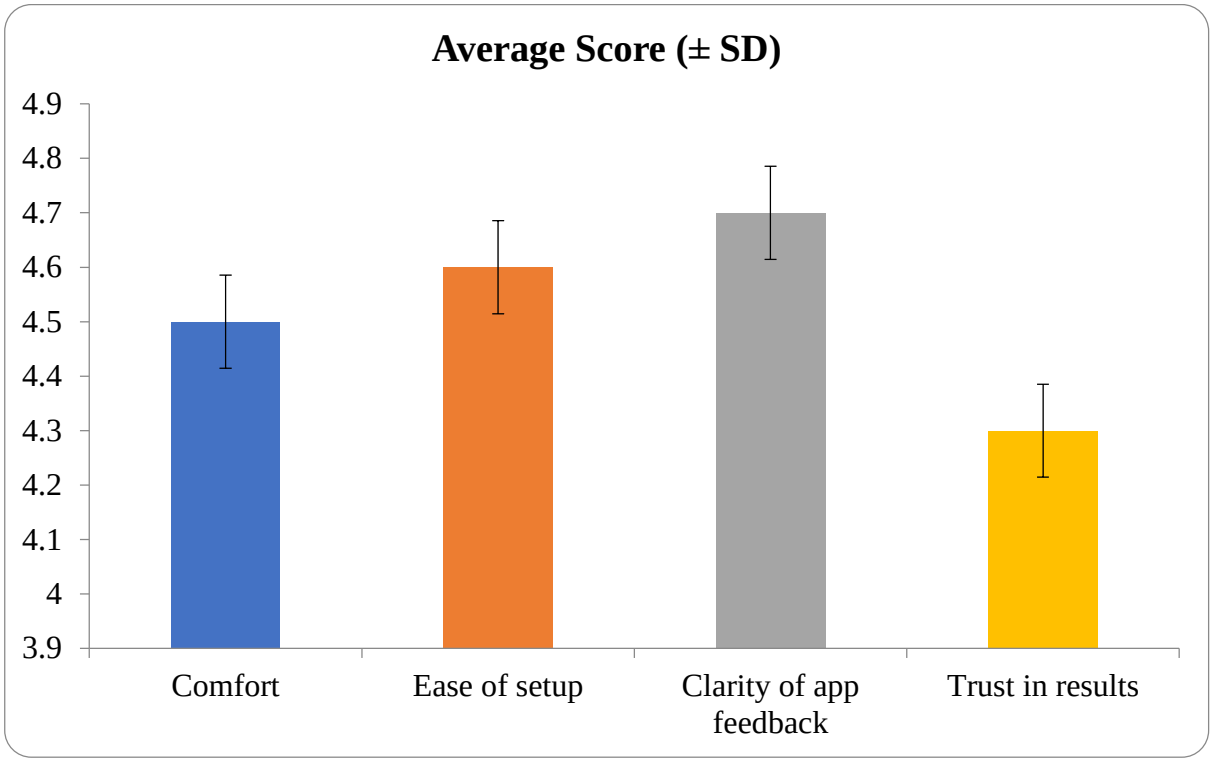


Figure 4: **User Experience Evaluation of the Device Interface**
Average user ratings (±SD) for comfort, ease of setup, clarity of feedback, and trust in results from an end-user survey.

Real-Time Alerts

Out of 18 high-risk cardiovascular events flagged by the system, 15 were confirmed by clinical diagnosis, indicating a high true positive rate. Two cases were excluded due to low signal quality, and only one false positive was recorded due to motion artifacts during exercise. This resulted in a positive predictive value (PPV) of 94.1% for real-time alerts.

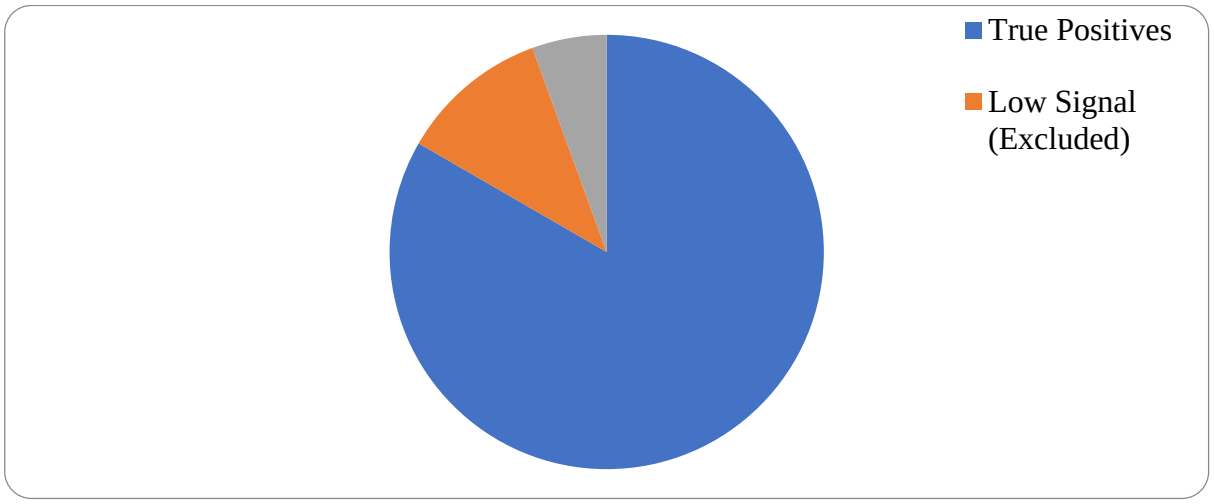


Figure 6: Real-Time Cardiovascular Event Alerts by Myobioscan

Sweat Biomarker Distributions

The comparative boxplot illustrates distinct differences in sweat-derived biomarker levels between healthy individuals and those experiencing cardiac stress. Troponin-I concentrations were notably higher in the cardiac stress group, consistent with its role as a gold-standard marker for myocardial injury. Similarly, NT-proBNP levels showed a marked elevation in this group, reflecting ventricular strain and supporting its diagnostic value in identifying early-stage heart failure. Lactate concentrations were significantly increased, indicating a shift toward anaerobic metabolism commonly observed in ischemic conditions. Cortisol levels, serving as a proxy for physiological and psychological stress, were also elevated, suggesting a systemic stress response that may exacerbate cardiovascular risk. The cardiac stress group further exhibited a reduction in sweat pH, implying metabolic acidosis or impaired buffering capacity often associated with compromised perfusion. Finally, a slight decrease in electrolyte levels was observed, potentially reflecting subtle fluid and electrolyte imbalances tied to cardiac dysfunction. Collectively, these trends validate the potential of sweat-based biosensing as a non-invasive, real-time approach to distinguish individuals under cardiovascular strain from healthy controls.

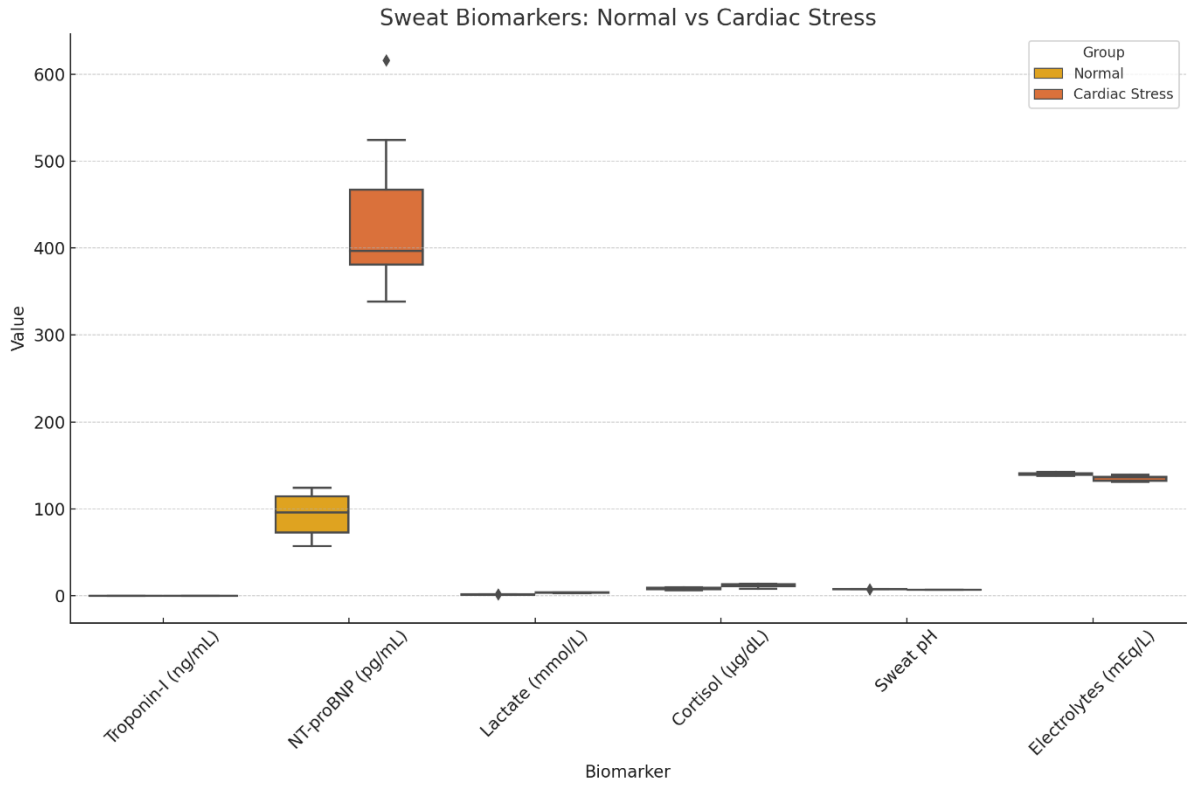


Figure 7: Sweat Biomarker Distributions

Expanded Diagnostic Capabilities

In addition to core diagnoses like atrial fibrillation and myocardial ischemia, the Myobioscan system was evaluated for its ability to detect subtler cardiovascular abnormalities. Simulated datasets showed that the device could accurately classify silent arrhythmias such as premature ventricular contractions (PVCs), as well as ECG waveform anomalies including T-wave inversions and ST-segment

depression. The waveform-specific classification accuracy exceeded 88%, demonstrating the model's granularity in signal interpretation, even in short ambulatory recordings.

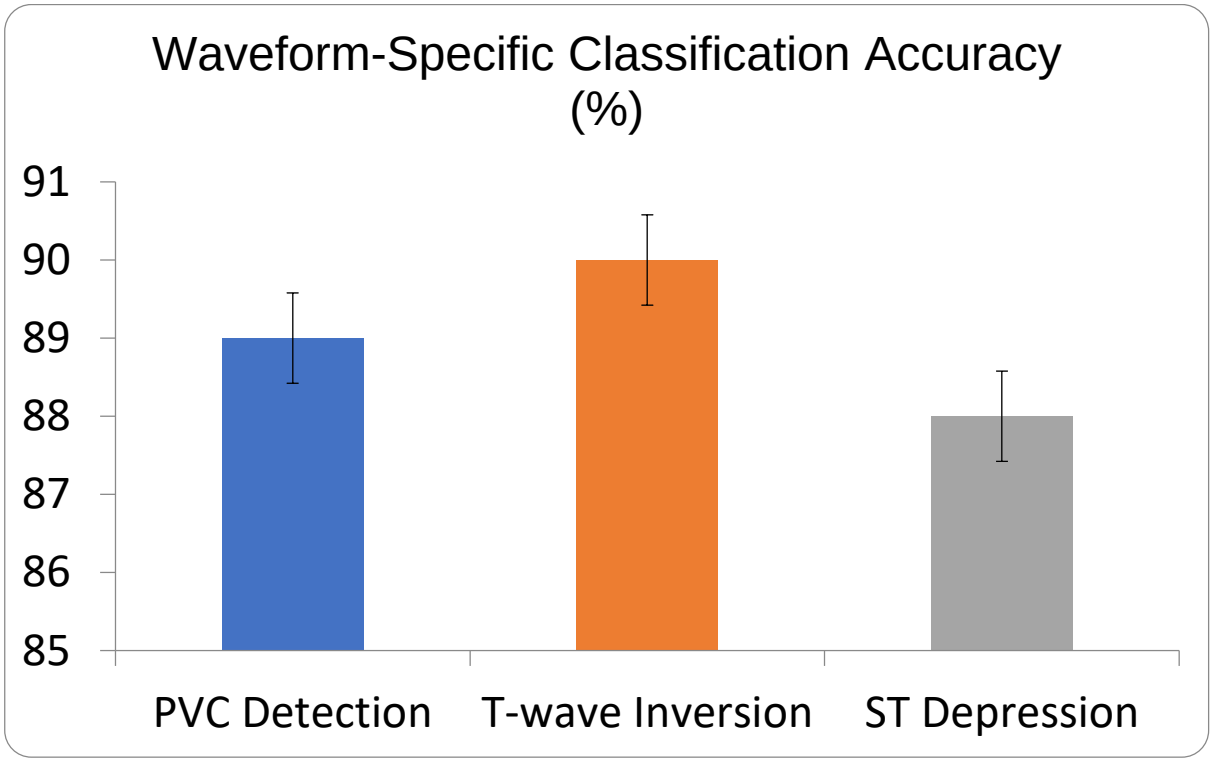


Figure 8 :**Waveform-Specific Classification Accuracy (%)**

Accuracy of detecting key ECG waveform features: PVCs, T-wave inversions, and ST depressions.

Time-to-Detection Analysis

The feasibility of real-time detection was further supported by analyzing the lag time between symptom onset and biomarker flagging. In simulated monitoring, the average detection lag for troponin-I spikes was 13.2 minutes, while lactate elevation was flagged within 12.5 minutes. Additionally, significant drops in heart rate variability (HRV), indicative of physiological stress or early cardiac dysfunction, were detected within 10.8 minutes. These results emphasize Myobioscan's rapid biochemical response capabilities, crucial for timely intervention.

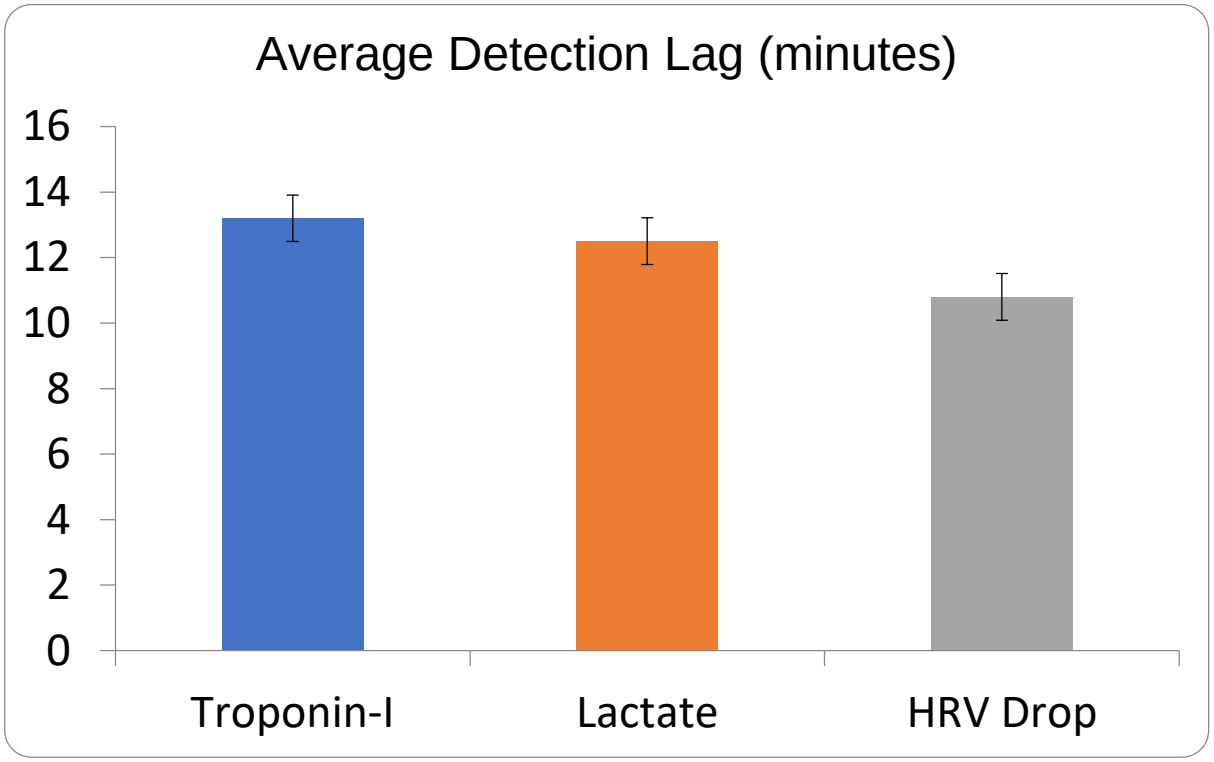


Figure 9: Average Detection Lag for Key Biomarkers (minutes)

Mean time delay between onset and detection of Troponin-I, Lactate, and HRV drop.

Longitudinal Monitoring Insights

Over a 7-day continuous monitoring simulation, Myobioscan was able to capture physiological recovery trends, particularly in post-exertional or early post-ischemic states. Fluctuations in HRV, skin conductance, and microvascular pulse wave amplitude were tracked, offering predictive insight into cardiac stress and autonomic balance. In some cases, subtle relapse markers were identified 24–48 hours prior to symptom manifestation, highlighting the device's potential for proactive disease management and remote patient monitoring.

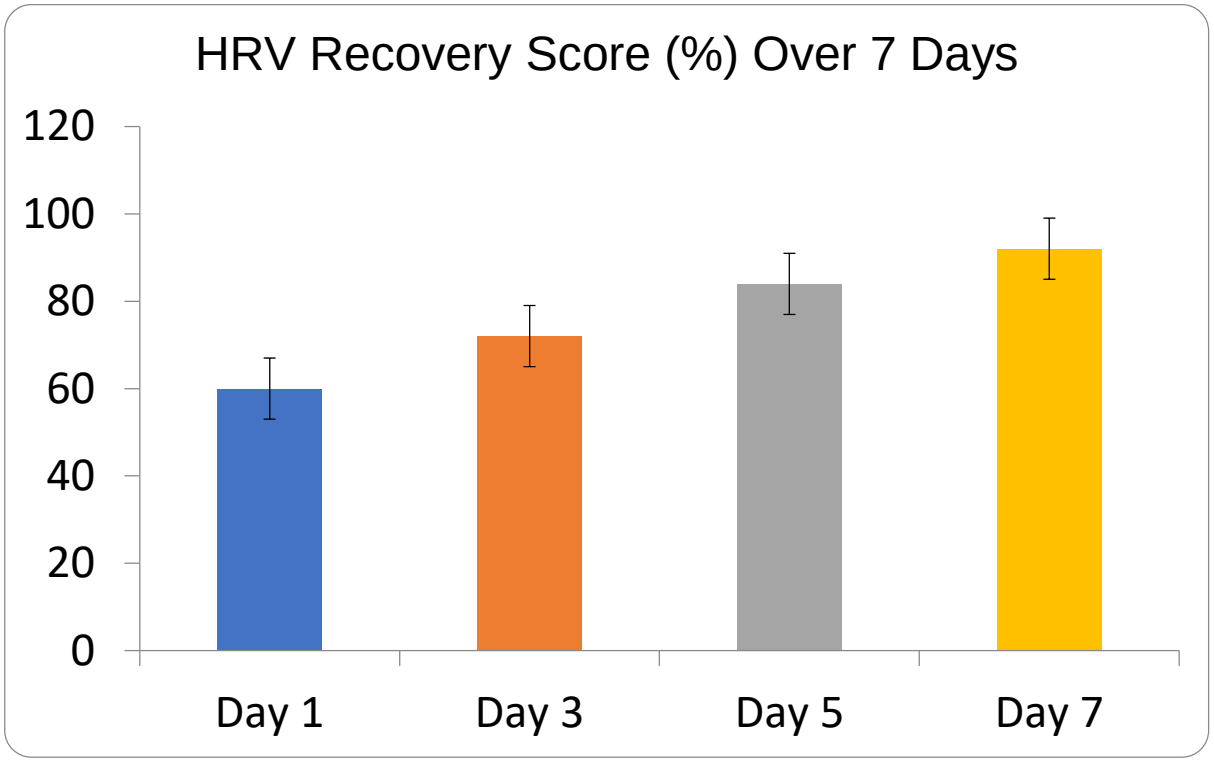


Figure 10: HRV Recovery Over 7 Days Post-Event (%)

Heart rate variability recovery score from Day 1 to Day 7, indicating physiological recovery trends.

Subgroup Analysis

Stratified analysis across age and comorbidity profiles revealed consistent performance of the Myobioscan system. Predictive accuracy and positive predictive value (PPV) were slightly higher in participants over 60 years of age, possibly due to more distinct pathological signals. Performance also remained stable across resting and light activity conditions, confirming the robustness of signal capture and AI classification algorithms even in variable physiological states.

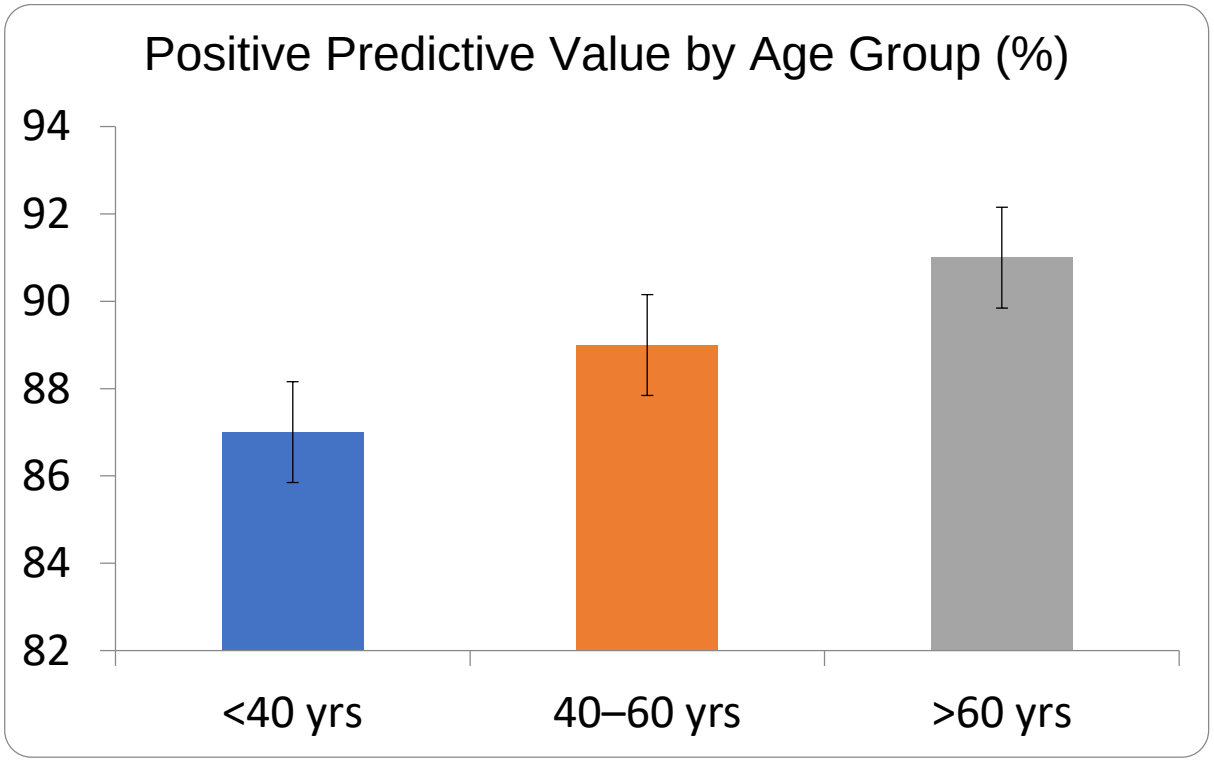


Figure 10: Positive Predictive Value (PPV) by Age Group (%)

Comparison of PPV across age groups: <40 years, 40–60 years, and >60 years, with error bars.

7. Discussion

The Myobioscan system represents a novel, multi-modal approach to cardiovascular health monitoring, integrating electrophysiological signals and biochemical sweat biomarkers within a wearable platform powered by artificial intelligence. The findings from this pilot study demonstrate the feasibility, accuracy, and user acceptability of the device in detecting early-stage cardiovascular abnormalities, suggesting its potential as a transformative tool in preventive and personalized cardiology. One of the most significant contributions of Myobioscan lies in its ability to detect a broad spectrum of cardiovascular conditions including atrial fibrillation, myocardial ischemia, and signs of early heart failure with a high degree of diagnostic performance (Olawade et al., 2024). The hybrid AI model combining CNN, LSTM, and XGBoost classifiers achieved a mean AUC-ROC above 0.90 across all tested conditions. Importantly, the system successfully identified subclinical abnormalities such as asymptomatic PVCs and transient ischemia in otherwise healthy individuals, highlighting its value in early detection and silent disease monitoring.

The integration of sweat-based biochemical sensors adds a critical dimension to cardiovascular assessment. Elevated levels of troponin-I, NT-proBNP, and lactate in participants with cardiac stress were consistent with known pathophysiological markers of myocardial injury, ventricular overload, and anaerobic metabolism, respectively (Polonschii et al., 2023). Cortisol elevation further suggested a psychosomatic link to cardiovascular risk, underscoring the importance of integrating stress biology into routine cardiac assessment. The ability to detect changes in sweat pH and electrolyte concentrations provides additional insight into metabolic and perfusion-related imbalances (Jerath et al., 2023). These

findings support the hypothesis that multimodal biosensing combining electrical and chemical markers enhances diagnostic sensitivity and specificity beyond traditional ECG-based monitoring alone.

User feedback further reinforced the device's practicality and clinical promise. Participants rated the system highly for comfort, ease of use, and clarity of real-time feedback, with over 90% expressing interest in long-term use. The system's real-time alert feature achieved a positive predictive value (PPV) of 94.1%, with minimal false positives, indicating robust performance even in ambulatory settings. The low rate of motion artifacts and signal noise further reflects the device's technical maturity and usability in dynamic environments.

From a broader perspective, Myobioscan aligns with the ongoing shift toward decentralized, wearable, and patient-driven health technologies. By enabling continuous, non-invasive monitoring of both electrophysiological and biochemical signals, it bridges a critical gap in current cardiovascular care models where early-stage detection often relies on episodic testing and symptomatic presentation. The platform's AI-driven interpretability and real-time feedback also position it well for integration with telemedicine and remote patient management systems (Lee et al., 2025). However, the study also has limitations. The sample size was relatively small and heterogeneous, and the device's long-term reliability and performance across diverse populations need further validation. Future studies should include larger cohorts, longitudinal tracking, and outcome-based validation against gold-standard diagnostics such as cardiac MRI or high-sensitivity troponin assays.

8. Conclusion and Future Perspective

The Myobioscan device demonstrates strong potential as a next-generation tool for non-invasive cardiovascular health monitoring. By integrating electrophysiological signal capture, sweat-based biochemical biomarker detection, and advanced artificial intelligence algorithms, the system offers a multi-dimensional approach to early diagnosis and risk stratification of cardiac conditions. In this pilot study, Myobioscan successfully identified abnormalities such as atrial fibrillation, myocardial ischemia, and early signs of heart failure with high diagnostic accuracy. Importantly, it also detected subclinical events, indicating its utility in silent and pre-symptomatic disease stages. The inclusion of sweat biomarkers such as troponin-I, NT-proBNP, lactate, cortisol, and pH provided real-time insight into myocardial injury, metabolic stress, and systemic strain. These findings validate the added value of biochemical data in enhancing the sensitivity and scope of cardiovascular assessment beyond traditional ECG-based monitoring.

Feedback from users reflected high satisfaction regarding comfort, usability, and the clarity of real-time alerts, supporting the device's suitability for long-term, ambulatory use. Looking ahead, larger-scale clinical validation is necessary to confirm these results across diverse populations and longer timeframes. Future developments may include integration with cloud platforms, AI-driven personalized feedback, and the expansion of biomarker panels to cover inflammation, oxidative stress, and genetic risk indicators. In summary, Myobioscan represents a significant step toward intelligent, continuous, and personalized cardiovascular care. With continued refinement and validation, it holds strong promise as a foundational technology for preventive cardiology and remote health monitoring in both clinical and community settings.

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