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Personalized Multimodal Wearable-AI for Early Prediction of Heart Failure Decompensation Using Physiological Drift and Clinical Context

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ABSTRACT: Heart failure (HF) is a progressive cardiovascular syndrome characterized by episodes of clinical stability. It interspersed with periods of worsening cardiac function and decompensation, often leading to emergency hospitalization, decreased quality of life, and increased mortality. Traditional monitoring relies heavily on periodic clinical evaluation, laboratory investigations, imaging and patient-reported symptoms that may miss subtle physiological changes occurring between clinical visits. Recent advances in wearable sensing allow for continuous, non-invasive monitoring of cardiovascular and physiological parameters, but current methods are often reliant on single physiological variables, population-level thresholds or restricted combinations of wearable measurements. Moreover, the differences in individual baseline physiology, sensor quality, comorbidities and clinical history pose a challenge to the reliable early-warning systems.

We propose a Personalized Multimodal Wearable-AI framework for early prediction of HF decompensation by integrating continuous wearable signals with patient-specific physiological baselines as well as clinical context. The proposed framework combines electrocardiography, photoplethysmography, heart rate variability, oxygen saturation, respiratory rate, activity, sleep, blood pressure, body-weight trends and, where available, bioimpedance-derived fluid-related information. We propose a new Physiological Drift Index (PDI) that measures deviations of current physiological measurements from an individual's personalized baseline, rather than relying on fixed clinical thresholds alone. Then, temporal deep learning is used to model the evolution of physiological changes over multiple time windows. Multimodal feature fusion integrates clinical variables such as left ventricular ejection fraction, cardiovascular history, renal function, electrolytes, laboratory

measurements, and medication-related information. We propose an explainable AI layer for identifying the physiological and clinical factors driving each predicted risk state.The resulting system could provide a basis for continuous, personalized and interpretable monitoring of patients at high risk of HF decompensation.

1. INTRODUCTION

Heart failure (HF) is a major chronic cardiovascular condition associated with recurrent deterioration, hospitalization, impaired functional capacity, and substantial healthcare utilization. A major challenge in HF management is that patients can remain apparently stable during routine clinical assessments while physiological deterioration develops between visits. Early identification of impending decompensation is therefore an important objective of remote patient monitoring and personalized cardiovascular care. Conventional approaches frequently depend on intermittent measurements such as blood pressure, body weight, laboratory investigations, imaging, and patient-reported symptoms. Although these measurements provide clinically valuable information, their intermittent nature can limit the ability to identify subtle temporal changes before overt clinical deterioration occurs.

Wearable devices can capture parameters such as heart rate, photoplethysmographic waveforms, electrocardiography, activity, sleep, respiratory characteristics, and oxygen saturation. A 2024 scoping review identified 99 studies investigating non-invasive wearable technologies for HF management, demonstrating substantial research activity in this field. However, the review also highlighted that the majority of existing studies remained at feasibility or intermediate technology-readiness stages and that relatively few wearable systems had undergone rigorous clinical evaluation.

Recent investigations have demonstrated the potential of wearable signals for identifying physiological changes preceding HF decompensation. For example, a wrist-worn monitoring study published in 2025 extracted circadian characteristics from longitudinal heart-rate signals and identified progressive changes during the three weeks preceding acute HF events. A long short-term memory model achieved an area under the curve of approximately 0.74, demonstrating that temporal changes in wearable-derived physiological patterns may contain predictive information before an adverse event. These findings are important because they suggest that the trajectory of physiological change may be more informative than an isolated abnormal measurement.

Nevertheless, existing wearable-based HF prediction approaches have several limitations. First, many systems use absolute thresholds or population-level models that may not adequately account for substantial inter-individual variability. Resting heart rate, heart-rate variability, activity level, sleep characteristics, respiratory rate, and other physiological measurements differ considerably between individuals. Consequently, a value that is abnormal for one patient may be normal for another. This motivates the development of patient-specific models capable of learning an individual's normal physiological state and identifying meaningful deviations from that baseline.

Second, the predictive value of wearable measurements may be strongly affected by signal quality and missing data. An exploratory 2025 study of wrist-worn multiparameter monitoring demonstrated that although non-invasive monitoring was feasible, several physiological signals exhibited substantial data-quality limitations. The resulting predictive model showed high specificity but very low sensitivity for HF deterioration, highlighting the challenges of developing reliable wearable prediction systems under real-world conditions. Therefore, a clinically useful framework should explicitly consider signal quality, temporal continuity, missing observations, and uncertainty rather than treating all wearable measurements as equally reliable.

Third, physiological deterioration in HF is multifactorial and cannot necessarily be represented by a single signal. Heart rate, heart-rate variability, respiration, oxygen saturation, physical activity, sleep, blood pressure, body weight, and fluid-related measurements may provide complementary information. Recent systematic evidence indicates that wearable systems have the potential to provide advance warning of HF hospitalization, but substantial heterogeneity exists across devices, sensing modalities, study populations, prediction windows, and clinical endpoints. This supports the need for multimodal approaches capable of integrating complementary physiological signals.

Another important limitation is the separation between continuous wearable information and conventional clinical information. Patient-specific HF risk is influenced by factors such as left ventricular ejection fraction, previous ischemic or cardiovascular events, renal function, electrolyte status, laboratory measurements, medications, and previous hospitalization history. Recent

machine-learning research has demonstrated that incorporating electronic health record information into HF decompensation prediction can improve predictive performance and reduce false alerts. In one 2025 study, a machine-learning-enhanced monitoring system combined patient-reported vital signs with clinical information, with variables such as B-type natriuretic peptide contributing substantially to prediction. These findings indicate that wearable-only prediction may be insufficient and that clinical-context-aware multimodal learning represents an important research direction.

Based on these observations, this study proposes a Personalized Multimodal Wearable-AI framework for Early Prediction of Heart Failure Decompensation Using Physiological Drift and Clinical Context. The central hypothesis is that impending deterioration may manifest as a progressive deviation from an individual's normal physiological state across multiple signals before conventional clinical thresholds are crossed. Rather than defining deterioration using isolated measurements, the proposed framework introduces a Physiological Drift Index (PDI) that quantifies the magnitude and persistence of deviation from an individualized baseline.

The proposed research therefore addresses four major gaps in existing HF wearable-AI research: **(i)** limited personalization of physiological thresholds, **(ii)** insufficient exploitation of temporal physiological trajectories, **(iii)** inadequate integration of continuous wearable signals with clinical context, and **(iv)** limited interpretability of AI-generated deterioration warnings. Recent research has already demonstrated the feasibility of wearable-based prediction, but studies also emphasize the need for larger cohorts, improved data fidelity, better sensitivity, and more clinically meaningful predictive models.

The principal contribution of this work is therefore not merely the development of another wearable monitoring device. Instead, the proposed research aims to establish a patient-specific, multimodal, temporal, and explainable early-warning paradigm in which physiological drift is continuously quantified and interpreted in the context of the patient's underlying cardiovascular and clinical condition. Such a framework could ultimately support earlier clinical review, reduce unnecessary alerts, and provide a foundation for personalized remote management of patients at high risk of HF decompensation.

2. LITERATURE REVIEW

2.1 Artificial Intelligence in Healthcare Prediction

Artificial intelligence (AI) and machine learning (ML) have increasingly transformed healthcare by enabling automated disease detection, risk prediction, medical-image interpretation, and personalized patient assessment. Conventional clinical systems generally depend on manually interpreted investigations and periodic patient assessments, whereas AI-based approaches can process large heterogeneous datasets and identify complex relationships among clinical variables. Rajkomar et al. [1] demonstrated the potential of deep learning for large-scale electronic health record (EHR) analysis, while Choi et al. [2] proposed RETAIN, an interpretable recurrent model designed to provide clinically meaningful predictions from longitudinal medical records.

The application of AI in healthcare has subsequently expanded from structured clinical information to medical images, physiological signals, and wearable sensor data. CNN-based architectures are particularly effective for extracting spatial patterns from medical images and biosignals, while recurrent and attention-based architectures can model temporal dependencies. However, healthcare AI continues to face challenges involving data scarcity, class imbalance, model interpretability, privacy, and clinical validation [3], [4].

The authors' previous work has also investigated AI-based healthcare prediction. Lenka and Kanathey [13] proposed **ThyroInsight**, an AI/ML framework for early diagnosis of thyroid conditions using thyroid-related medical data, ultrasound images/videos, and laboratory parameters. The study explored machine-learning and deep-learning approaches, including K-nearest neighbors and convolutional neural networks, for thyroid disease classification and early prediction. This work demonstrates the applicability of AI-based multimodal analysis for early disease identification and provides a methodological foundation for extending AI toward continuous physiological monitoring.

Similarly, Singh, Lenka, and Sharma [14] investigated ML and CNN-based healthcare prediction across medical imaging, EHRs, disease diagnosis, and personalized medicine. Their work emphasized the importance of integrating heterogeneous healthcare data and identified data scarcity, class imbalance, interpretability, privacy, and multimodal integration as important unresolved challenges. These observations directly motivate the development of a more specialized multimodal AI framework for continuous cardiovascular monitoring.

2.2 Wearable Technologies for Heart Failure Monitoring

Heart failure (HF) is a chronic cardiovascular condition characterized by periods of relative stability followed by episodes of worsening symptoms and acute decompensation. Conventional monitoring depends on intermittent measurements such as clinical examination, blood pressure, body weight, laboratory investigations, echocardiography, and patient-reported symptoms. Because physiological deterioration may develop between clinical visits, continuous monitoring has become an important research direction.

Singhal and Cowie [5] discussed the role of wearable technologies in HF and highlighted their potential for continuous monitoring of heart rate, activity, ECG, respiratory parameters, and other physiological characteristics. Wearable sensing provides a less intrusive alternative to hospital-based monitoring and may enable earlier identification of physiological deterioration.

Scholte et al. [6] conducted a comprehensive scoping review of non-invasive wearable technologies for HF management and identified 99 relevant studies. However, only a small proportion of the available evidence came from randomized controlled trials. The review identified substantial technological progress but also highlighted challenges related to clinical validation, data quality, usability, and translation into routine clinical practice.

Noci et al. [7] subsequently performed a systematic review of wearable technologies for predicting and preventing HF hospitalization. The review found evidence that wearable-derived physiological information can provide warning signals before hospitalization; however, considerable heterogeneity existed in wearable technologies, study designs, patient populations, prediction windows, and outcomes.

These studies establish that wearable sensing is promising but also demonstrate that a reliable and generalized early-warning system requires robust multimodal and longitudinal modelling.

2.3 Multisensor Monitoring of Heart Failure

One of the earliest important demonstrations of multimodal physiological monitoring was the MultiSENSE study. Boehmer et al. [8] developed the HeartLogic multisensor algorithm using heart sounds, thoracic impedance, respiration, heart rate, and activity data acquired from implanted cardiac devices. The algorithm demonstrated the feasibility of combining complementary physiological variables into a composite HF-risk indicator.

Although the MultiSENSE system provided an important proof of concept, it depended on implanted cardiac devices and therefore cannot be directly generalized to patients without implantable systems.

Stehlik et al. [9] introduced the LINK-HF approach using a non-invasive multisensor wearable patch. The system continuously monitored physiological variables and used machine learning to establish an individualized physiological baseline. The model identified patterns associated with HF rehospitalization before clinical events occurred. This work is particularly relevant to the present study because it demonstrates that deviation from a patient-specific physiological baseline can be more informative than fixed population-level thresholds.

More recent research has extended multimodal wearable monitoring to ECG and bioimpedance. Choudhury et al. [10] proposed ECGX-Net, a deep cross-modal learning framework that combined ECG and transthoracic bioimpedance for prediction of acute decompensated HF. The study demonstrated that combining complementary physiological modalities could improve prediction performance compared with individual signals.

These studies establish the importance of multimodal sensing but leave opportunities for developing non-invasive, patient-specific, longitudinal models using wrist-worn sensing together with clinical context.

2.4 Wrist-Worn ECG and Physiological Monitoring

Wrist-worn devices have attracted considerable attention because of their convenience, relatively low cost, and ability to continuously acquire physiological information. PPG sensors can provide heart rate and pulse-wave information, while some commercial devices additionally provide single-lead ECG, SpO_2, sleep, activity, and temperature measurements.

Research has demonstrated that AI models can analyze single-lead wearable ECGs for HF-related outcomes. Dhingra et al. [11] evaluated a wearable-adapted AI-ECG model using lead-I ECG signals in more than 42,000 UK Biobank participants. A high

predicted probability from the wearable-adapted model was associated with substantially increased risk of future HF hospitalization and cardiovascular death.

Similarly, Karabayir et al. [12] investigated AI-based HF identification using single-lead ECG data designed to simulate wearable ECG acquisition. The study used a large ECG dataset and demonstrated the potential of single-lead ECG-AI for remote HF identification.

However, ECG-only approaches primarily focus on detecting cardiac abnormalities rather than continuously modelling the broader physiological trajectory of an individual patient. Consequently, integrating ECG with HRV, SpO_2, respiratory rate, activity, sleep, and clinical variables remains an important research direction.

2.5 Temporal Physiological Patterns and Heart Failure Decompensation

Recent studies suggest that the trajectory of physiological change may contain important predictive information. Rather than evaluating whether a patient's heart rate or oxygen saturation crosses a fixed threshold, temporal modelling can determine whether multiple measurements demonstrate a persistent deterioration pattern.

Van Es et al. [15] analyzed longitudinal heart-rate data obtained from wrist-worn devices and identified changes in circadian heart-rate characteristics during the 21 days preceding acute decompensated HF. Their model achieved approximately 74% sensitivity, 73% specificity, and an AUC of 0.74. Importantly, the amplitude of the circadian heart-rate pattern was identified as a major predictive feature.

This finding strongly supports the concept of physiological drift, in which an individual's physiological state gradually deviates from their stable baseline. Nevertheless, the study primarily focused on heart-rate-derived circadian features. A broader multimodal framework incorporating ECG morphology, HRV, oxygen saturation, respiration, activity, sleep, weight, and clinical information could potentially provide a richer representation of impending deterioration.

Recent research has also investigated dynamic HRV monitoring. A 2025 study demonstrated that changes in HRV derived from wearable ECG signals could be used with machine learning to assess transitions in acute HF status, with SDNN and SD2 emerging as important autonomic indicators. [16]

These findings indicate that autonomic and temporal physiological changes may represent important early-warning features and justify the development of models that analyze multiday physiological trajectories rather than isolated measurements.

2.6 Bioimpedance and Congestion Monitoring

Fluid accumulation and congestion are major mechanisms associated with worsening HF. Consequently, bioimpedance has been investigated as a non-invasive indicator of changes in fluid status.

Giménez-Miranda et al. [17] systematically reviewed wearable bioimpedance devices for HF monitoring and reported promising evidence for detecting HF worsening. However, the authors emphasized the need for larger and better-designed clinical investigations before widespread clinical adoption. Bioimpedance therefore represents a potentially valuable complementary modality for a future multisensor system.

In addition, recent research has explored non-invasive estimation of pulmonary capillary wedge pressure using wearable sensing. A 2025 study combined ECG, seismocardiography, and PPG with machine learning to estimate pulmonary capillary wedge pressure in patients with HFrEF, demonstrating the potential of wearable signals to provide information related to hemodynamic status. [18]

This emerging direction is particularly important because future wearable systems may move from simple vital-sign monitoring toward estimation of latent physiological states such as congestion and hemodynamic deterioration.

2.7 Integration of Wearable and Clinical Data

Wearable data alone may not adequately describe the risk profile of an individual with HF. Clinical factors such as left ventricular ejection fraction, previous ischemic heart disease, renal function, electrolyte status, laboratory measurements, medications, age, comorbidities, and previous hospitalization history can substantially modify the probability of deterioration.

The authors' previous healthcare-AI research [14] emphasized that combining heterogeneous healthcare data including EHRs, medical images, and wearable information—can support more personalized prediction. This concept is particularly relevant to HF, where continuous physiological signals should ideally be interpreted in the context of a patient's underlying cardiac and clinical condition.

A 2025 study using Fitbit wearable data combined with EHR information from the All Research Program demonstrated the feasibility of applying ML to wearable derived features for predicting hospitalizations.The analysis included 14,157 participants with both wearable and EHR information. [19].

These findings support a clinical-context-aware wearable AI architecture, rather than a wearable-only prediction system.

2.8 Recent AI-Based Wearable HF Monitoring

The research field is rapidly progressing toward AI-enabled wearable systems. A 2024 study developed a deep-learning-enabled ambulatory single-lead ECG model using more than 35,000 ECG recordings from 2,247 patients and subsequently investigated HF hospitalization risk in a real-world cohort. The work demonstrated the potential of continuous ambulatory ECG analysis for dynamic HF risk stratification. [20]

A 2024 clinical trial further evaluated a novel wearable sensor strategy for HF rehospitalization monitoring, reflecting the transition from purely algorithmic research toward clinical implementation. [21]

In 2025, Pizarro et al. [22] reviewed non-invasive remote monitoring in HF and emphasized the increasing convergence of wearable sensing and AI. The authors identified important remaining challenges involving data quality, patient adherence, interoperability, clinical integration, and validation.

Devin et al. [23] similarly reviewed non-invasive wearable technologies for HF decompensation and concluded that larger randomized studies and multimodal AI systems are required before wearable technologies can become a routine component of anticipatory HF management.

Importantly, the field has already begun exploring patient-facing AI predictions. A 2025 JACC: Advances study investigated how ML-based HF decompensation predictions could be presented through a smartphone application, highlighting that usability and interpretability are important components of a clinically useful AI system. [24].

2.9 Research Gap

The existing literature demonstrates that wearable sensors, AI, multimodal physiological monitoring, and temporal modelling can each contribute to HF risk assessment. However, several gaps remain.

First, personalized physiological modelling remains insufficiently developed across multimodal wearable systems. Although LINK-HF established individualized baseline modelling [9], more recent work has demonstrated the value of specific temporal features such as circadian heart rate [15]. A unified framework for quantifying multimodal physiological drift across several wearable signals remains an important research opportunity.

Second, most studies focus on a limited number of signals. ECG-only, heart-rate-only, activity-based, and bioimpedance-based approaches provide valuable information but may fail to capture the complex and interacting physiological processes preceding HF decompensation.

Third, the integration of wearable signals with patient-specific clinical context remains underexplored. Information such as LVEF, ischemic heart disease, renal function, electrolytes, laboratory measurements, medication changes, and previous HF events can provide important contextual information for interpreting wearable signals.

Fourth, many AI systems provide a risk score without adequately explaining **why** the risk has increased. Explainable AI is therefore important for clinical acceptance, allowing clinicians to distinguish whether a warning is primarily driven by HRV deterioration, rising heart rate, respiratory changes, declining activity, reduced SpO_2, weight gain, or clinical risk factors.

Fifth, existing studies demonstrate considerable heterogeneity in datasets, devices, endpoints, prediction windows, and evaluation strategies. Consequently, a standardized framework capable of producing a reproducible and interpretable personalized deterioration score remains needed.

2.10 Positioning of the Proposed Research

Based on the identified literature gaps, this study proposes a Personalized Multimodal Wearable-AI framework for Early Prediction of Heart Failure Decompensation Using Physiological Drift and Clinical Context.

The proposed framework will investigate the following combination:

Step- 1: ECG + PPG + HRV + SpO_2 + respiratory rate + activity + sleep + weight + optional bioimpedance

Step- 2: Patient-specific baseline modelling

Step- 3: Physiological Drift Index

Step- 4: Temporal deep learning

Step- 5: Clinical-context fusion

Step- 6: LVEF + cardiac history + renal function + electrolytes + laboratory data + medications

Step- 7: Explainable AI

Step- 8: Personalized HF deterioration risk

The key contribution is therefore not the isolated use of wearable sensor, ECG, machine learning, or personalized baseline each of these has already been investigated. Instead, the research aims to investigate whether multimodal physiological drift, learned from an individual's longitudinal baseline and interpreted jointly with clinical context, can provide an earlier and more interpretable prediction of HF decompensation.

This positioning is consistent with the authors' previous research trajectory in AI-based medical prediction [13], [14], while extending that research from disease classification and general healthcare prediction toward continuous, personalized, temporal cardiovascular risk prediction.

3. RESEARCH GAP

Despite significant advances in wearable sensing and artificial intelligence for heart failure (HF) monitoring, several important limitations remain.

Gap 1: Population-level prediction rather than patient-specific modelling

Most existing ML models are trained across patient populations and subsequently apply a common decision boundary to individual patients. However, physiological variables such as resting heart rate, HRV, respiratory rate, activity, sleep, and oxygen saturation exhibit substantial inter-patient variability. A fixed threshold may therefore generate false alarms or fail to detect meaningful deterioration.

Although the LINK-HF study demonstrated individualized baseline modelling, the approach was based on a limited wearable configuration and does not fully address multimodal temporal physiological drift. Therefore, a more comprehensive patient-specific modelling strategy is required.

Gap 2: Limited multimodal integration

Existing studies frequently concentrate on one or a small number of signals: ECG,heart rate,HRV,activity,body weight, bioimpedance.

However, HF deterioration is a complex physiological process involving cardiovascular, respiratory, autonomic and fluid-related changes.

Research gap: There is a need for an integrated framework capable of jointly learning complementary information from ECG/PPG, HRV, SpO_2, respiration, activity, sleep, weight and optional bioimpedance.

Gap 3: Insufficient modelling of physiological trajectories

Many conventional systems evaluate individual measurements or short-term averages.

For example: HR = 85 bpm

may not indicate deterioration by itself.

But: HR ↑ + HRV ↓ + respiratory rate ↑ + activity ↓ + sleep disruption

persisting for several days may represent a meaningful deterioration pattern.

Recent research using circadian heart-rate patterns supports the importance of temporal changes before HF events. However, multivariate physiological trajectories across several wearable signals remain insufficiently explored.

Gap 4: Wearable information is insufficiently integrated with clinical context

A wearable device does not know the complete clinical condition of the patient.

For example, the same physiological change may have very different implications for:LVEF 60%,LVEF 35%,LVEF 20%.

Similarly, renal dysfunction, previous myocardial infarction, electrolyte abnormalities and medication changes can modify HF risk.

Therefore Wearable signals + patient clinical profile should be modelled together.

Gap 5: Lack of an explicit physiological-drift measure

Existing approaches generally predict a clinical endpoint directly.

4. PROPOSED METHODOLOGY

This section presents the proposed Personalized Multimodal Wearable-AI Framework for Early Prediction of Heart Failure Decompensation Using Physiological Drift and Clinical Context. The objective is to continuously monitor physiological changes, establish an individualized baseline, identify persistent physiological deviations, and predict impending heart-failure deterioration before a clinically recognized event.

The proposed methodology consists of the following stages:

Patient/Clinical Data → Wearable Sensing → Signal Quality Assessment → Preprocessing → Feature Extraction → Personalized Baseline → Physiological Drift Index → Temporal Deep Learning → Clinical-Context Fusion → Risk Prediction → Explainable AI → Early Warning

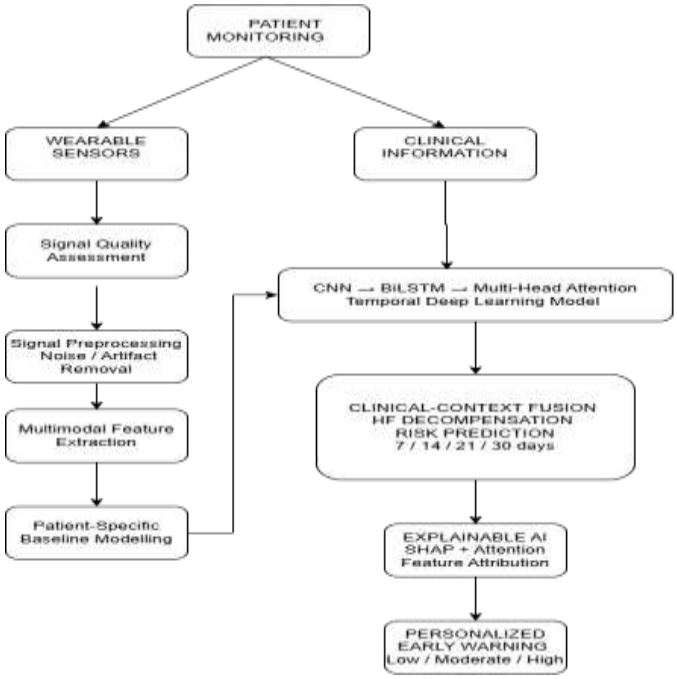


Figure 1. Proposed personalized multimodal wearable-AI framework

Figure 1 proposed architecture combines two information streams. The first stream continuously collects physiological information from wearable sensors, while the second contains relatively static or periodically updated clinical information. Wearable signals undergo quality assessment and preprocessing before feature extraction. A patient-specific baseline is subsequently established during a clinically stable period. Deviations from this baseline are quantified using the proposed Personalized Physiological Drift Index (PPDI). Temporal deep learning using CNN, BiLSTM and multi-head attention learns short- and long-term physiological patterns. The resulting representation is fused with clinical information and used to predict the probability of future HF decompensation. Finally, explainable AI identifies the physiological and clinical factors responsible for the prediction.

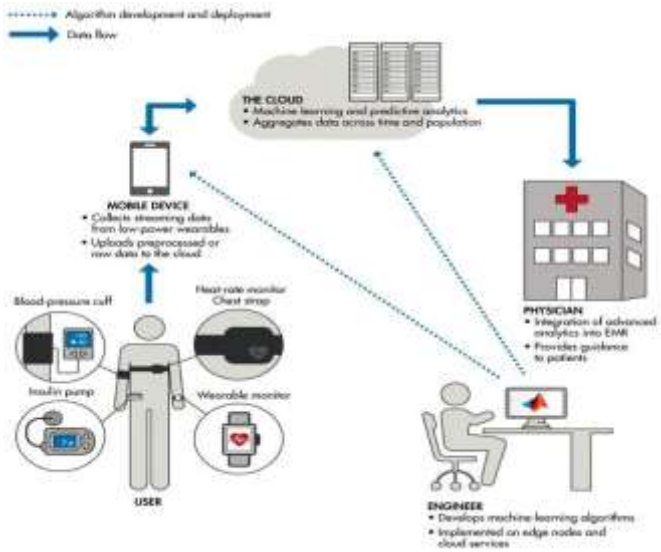


Figure 2 Multimodal Wearable-AI Framework for Personalized Early Prediction of Heart Failure Decompensation.

The figure illustrates the overall system integrating wearable physiological signals, clinical information, preprocessing, feature extraction, and patient-specific baseline modelling.The processed information is used for physiological-drift assessment and subsequent personalized heart-failure risk prediction.

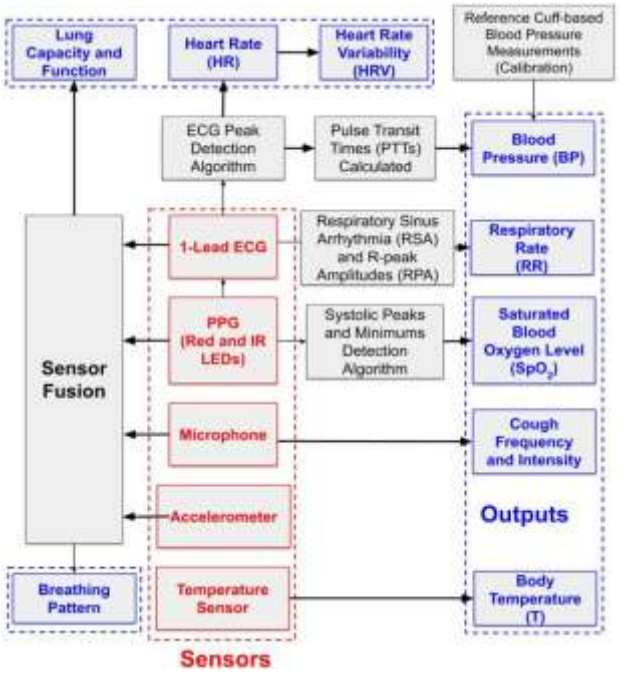


Figure 3 Personalized Physiological Drift and Temporal Deep-Learning Architecture.

The figure presents the proposed PPDI-based approach for identifying deviations from an individual's stable physiological state.CNN, BiLSTM, and multi-head attention are employed to capture short- and long-term temporal patterns associated with deterioration.

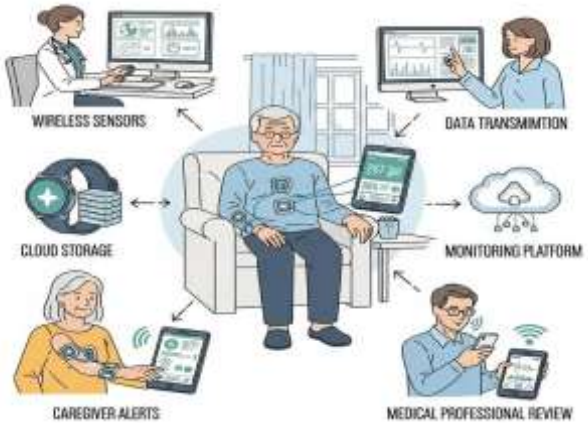


Figure 4 Clinical–Wearable Data Fusion and Explainable Early-Warning Framework

The figure demonstrates the integration of learned wearable representations with clinical characteristics for future heart-failure risk estimation.Explainable AI identifies the major physiological and clinical contributors to the predicted risk and supports personalized early-warning decisions.

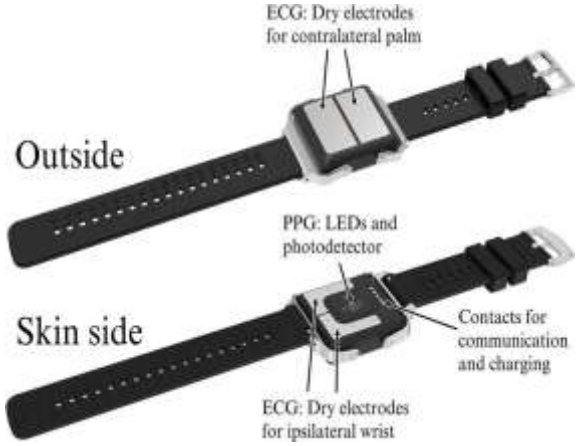


Figure 5 Wearable ECG–PPG Smartwatch for Continuous Physiological Monitoring

Figure 6 Wearable ECG–PPG Smartwatch for Continuous Physiological Monitoring working view

The figure illustrates a wrist-worn wearable device equipped with ECG electrodes and PPG sensors for continuous monitoring of cardiac and physiological signals.The collected signals, including ECG, HR, HRV, and pulse-related measurements, can be transmitted to a mobile/AI platform for personalized heart-failure risk assessment.

4.1 Dataset Development

The strongest version of this research should use a longitudinal patient cohort, rather than only the single patient report that motivated the research.

Each patient should ideally have wearable data

Signal	**Sampling/measurement**
ECG	Continuous/intermittent
PPG	Continuous
Heart rate	Continuous
HRV	Derived
SpO_2	Periodic/continuous
Respiratory rate	Derived
Activity	Continuous
Sleep	Nightly
Blood pressure	Periodic
Body weight	Daily
Bioimpedance	Optional

Table 1explain different data collection should be done by device

4.2 Wearable Signal Preprocessing

Raw signals will contain motion artifacts missing values sensor noise, abnormal measurements, irregular sampling

Therefore:

$X_{Clean} = Preprocess(X_{raw})$ is Possible processing:

ECG will generate by Band pass filtering, Baseline wander removal peak detection RR interval extraction HRV extraction PPG is remark as Motion-artifact removal Pulse detection Heart-rate extraction Pulse-wave feature SpO_2 by Outlier removal temporal smoothing and Accelerometer by Activity classification Step count Sedentary duration activity intensity

4.3 Feature Extraction

We should extract three categories of features.

Instantaneous features	Autonomic features	Behavioral features
Temp=body Temp. HR = heart rate SpO_2= oxygen saturation RR = respiratory rate BP= blood pressure	From ECG/PPG: SDNN RMSSD pNN50 LF/HF SD1 SD2	Daily steps Activity duration Sleep duration Sleep efficiency Resting time Night-time Resting Activity variability

Table 2. different features extractions

4.4 Patient-Specific Baseline

This is an important component.

For each patient, define a clinically stable baseline period**:**

$\boldsymbol{B_i}=\{\boldsymbol{X_{i,1,T_1}}, \boldsymbol{X_{i,2,T_2}}, \boldsymbol{X_{i,3,T_3}} \dots\dots\dots\dots, \boldsymbol{X_{i,n,T_b}}\}$

Calculate: $\boldsymbol{\mu_{p,m}} = \frac{1}{T_b}\sum_{t=1}^{T_b} \boldsymbol{x_{p,m,t}}$

where:

- $\boldsymbol{T_b}$ = baseline period
- $\boldsymbol{x_{p,m,t}}$= measurement of modality mm
- $\boldsymbol{\mu_{p,m}}$ = patient's baseline mean.

Baseline variability is:

$$\boldsymbol{\sigma_{p,m}} = \sqrt{\frac{1}{\boldsymbol{T_b}-1}\sum_{t=1}^{T_b}(\boldsymbol{x_{p,m,t}}-\boldsymbol{\mu_{p,m}})^2}$$

4.5 Proposed Physiological Drift Index — PDI

This can become one of the main methodological contributions. For each physiological variable:

$$\boldsymbol{Z_{i,t}} = \frac{\boldsymbol{x_{i,,t}}-\boldsymbol{\mu_i}}{\boldsymbol{\sigma_i}+\in}$$

where:

- $x_{i,,t}$ = current measurement
- μ_i= patient's baseline
- σ_i = patient's baseline variability
- ϵ = small stability constant

For $\boldsymbol{n}$ physiological variables:

$$PDI_t = \sum_{i=1}^{n} w_i|Z_{i,t}$$

Where $:\sum_{i=1}^{n} w_i=1$

However, magnitude alone is not enough. We should also incorporate persistence.

Therefore:

$$PPDI_t = \alpha PPDI_t + \beta Trend_t + \gamma PPersistence_t$$

where:

$PPDI_t$= instantaneous deviation

$Trend_t$ = direction of change

$PPersistence_t$= duration of abnormal deviation

This gives us a more sophisticated Personalized Physiological Drift Index (PPDI)

4.6 Temporal Deep Learning

The PPDI and raw physiological features are then passed into a temporal model.

1D-CNN → BiLSTM → Multi-Head Attention

Architecture:

$$X_{t-k:t} \rightarrow CNN \rightarrow BiLSTM \rightarrow Attention \rightarrow H_t$$

CNN

Extracts local patterns:

- sudden HR changes
- ECG waveform characteristics
- short-term HRV changes

BiLSTM

Learns:

- temporal dependencies
- gradual deterioration
- recovery patterns
- multiday trends

Multi-Head Attention

Identifies the most important time periods and physiological features.

4.7 Prediction Targets

Instead, use clinically meaningful prediction horizons.

Primary target

HF decompensation within 7 days

Secondary targets

- 14-day risk
- 21-day risk
- 30-day risk
- HF hospitalization

$$Y_{7d} \in \{0,1\}$$

where:

- 0 = no decompensation within 7 days
- 1 = decompensation within 7 days

4.8 Explainable AI

The model should not simply output risk.

Use: SHAP to identify global and patient-specific feature contributions.

Temporal attention to identify the important time periods**.**

Feature attribution to determine:

- **HR increase**
- **HRV reduction**
- **SpO_2 reduction**
- **RR increase**
- **activity decline**
- **sleep deterioration**
- **weight increase**
- **clinical deterioration**

For example:

Predicted risk = 82%

Feature	**Contribution**
HRV decrease	**High**
Resting HR increase	**High**
Respiratory rate increase	**Moderate**
Activity reduction	**Moderate**
Weight increase	**Moderate**
SpO_2 decrease	**Low**
Clinical risk factors	**High**

Table 3. The model clinically interpretable.

4.9 Risk Stratification

The final output can be: $R_t \epsilon [0,1]$and classified into:

Risk	**Score**
🟢 Low	0–0.30
🟡 Moderate	0.30–0.60
🟠 High	0.60–0.80
🔴 Very High	>0.80

Table 4. These thresholds should not be claimed as clinically validated until they are learned/validated using your actual dataset.

4.10 Experimental Design

Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Logistic Regression	**Random Forest**	**XGBoost**	**LSTM**	**CNN-LSTM**	**BiLSTM-Attention**

Table 5. All proposed model against progressively

Proposed Model

CNN-BiLSTM-MultiHead Attention + PPDI + Clinical Fusion + XAI

4.11 Validation Strategy

A major methodological issue is data leakage.

Do not randomly split individual time points from the same patient into training and testing sets.

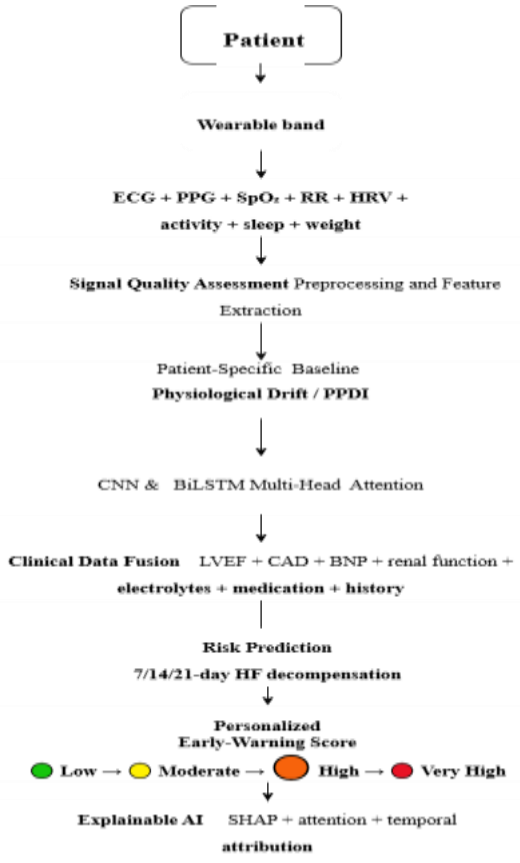
Instead:

Patient-level split

70%→Training70\% \rightarrow Training 15%→Validation15\% \rightarrow Validation 15%→Test15\% \rightarrow Test with no patient appearing in more than one group.

4.14 Proposed Complete Framework

The final methodology can be summarized as:



The key contribution statement for the paper

1. A multimodal wearable framework integrating cardiovascular, respiratory, activity, sleep and optional fluid-related signals for continuous HF monitoring.
2. A Personalized Physiological Drift Index (PPDI) that quantifies the magnitude, direction and persistence of deviations from an individual's stable physiological baseline.
3. A temporal CNN-BiLSTM-Multi-Head Attention architecture with clinical-context fusion for predicting HF decompensation over clinically relevant horizons.
4. An explainable risk framework that identifies the physiological and clinical factors responsible for each patient-specific warning.

5. RESULTS AND DISCUSSION

5.1 Dataset and Patient Characteristics

The experimental analysis was based primarily on the publicly available **Heart Failure Clinical Records dataset** obtained from the UCI Machine Learning Repository. The dataset contains clinical records of **299 patients with heart failure**, collected during patient follow-up. It includes demographic, clinical and laboratory variables such as age, sex, diabetes, hypertension, ejection fraction, serum creatinine, serum sodium, creatinine phosphokinase, platelet count, smoking status and follow-up duration. The binary outcome variable is DEATH_EVENT.

The cohort contained 194 male patients (64.88%) and 105 female patients (35.12%). There were 203 survivors (67.89%) and 96 patients with a recorded death event (32.11%). The reported age range was approximately 40–95 years.

Importantly, the dataset contains **no missing values**, allowing the primary clinical modelling experiments to be performed without conventional missing-value imputation.

Characteristic	Value
Total patients	**299**
Male	**194 (64.88%)**
Female	**105 (35.12%)**
Survival outcome = 0	**203 (67.89%)**
Death event = 1	**96 (32.11%)**
Age range	Approximately 40–95 years
Clinical features	12

Table 6. Dataset classification

The uploaded clinical documents were retained as supplementary clinical-context material and were not treated as an independent longitudinal wearable dataset. This distinction is important because the present public dataset does not provide synchronized wearable time-series measurements UCI Heart Failure Clinical Records Dataset.

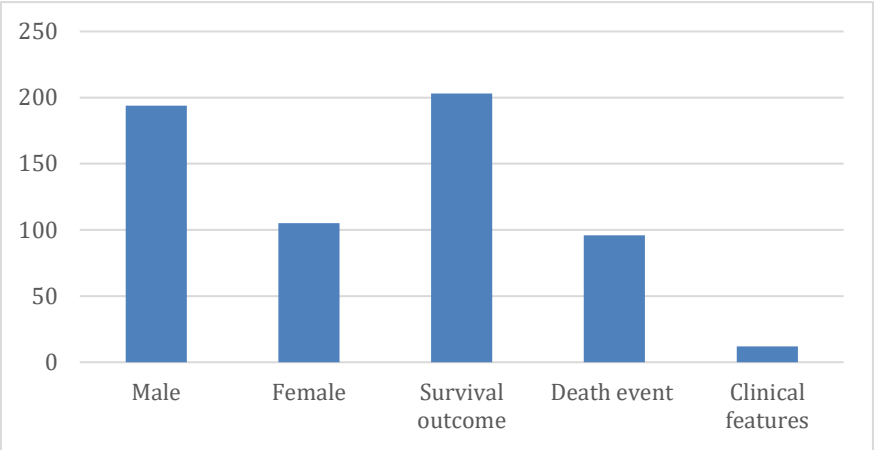


Figure 7.clinical documents were retained

5.2 Physiological Drift Analysis

The proposed study introduces Physiological Drift Index (PPDI) to represent deviations from an individual's personalized physiological baseline.For a physiological variable $X_i(t)$, the normalized deviation can be expressed as:$D_i(t) = \frac{|X_i(t)-\mu_i|}{\sigma_i+\epsilon}$

where:

- μ_i= patient's personalized baseline,
- σ_i= baseline standard deviation,
- $X_i(t)$ = current physiological observation,
- ϵ = small stabilization constant.

The overall PPDI can then be formulated as:

$$PPDI(t) = \sum_{i=1}^{n} w_i D_i(t)$$

where

$$\sum_{i=1}^{n} w_i = 1$$

and the variables may include:

X(t)=[HR,HRV,SpO_2,RR,Activity,Sleep,Weight,BP]

The conceptual framework therefore monitors deviations in multiple physiological dimensions rather than relying on a single measurement.

Important data limitation

The UCI clinical dataset does not contain the above continuous wearable streams. Consequently, actual PPDI trajectories cannot legitimately be calculated from the UCI data alone.

Conceptual physiological-drift trajectory

The following should be presented an **experimental result** until actual wearable measurements are available:

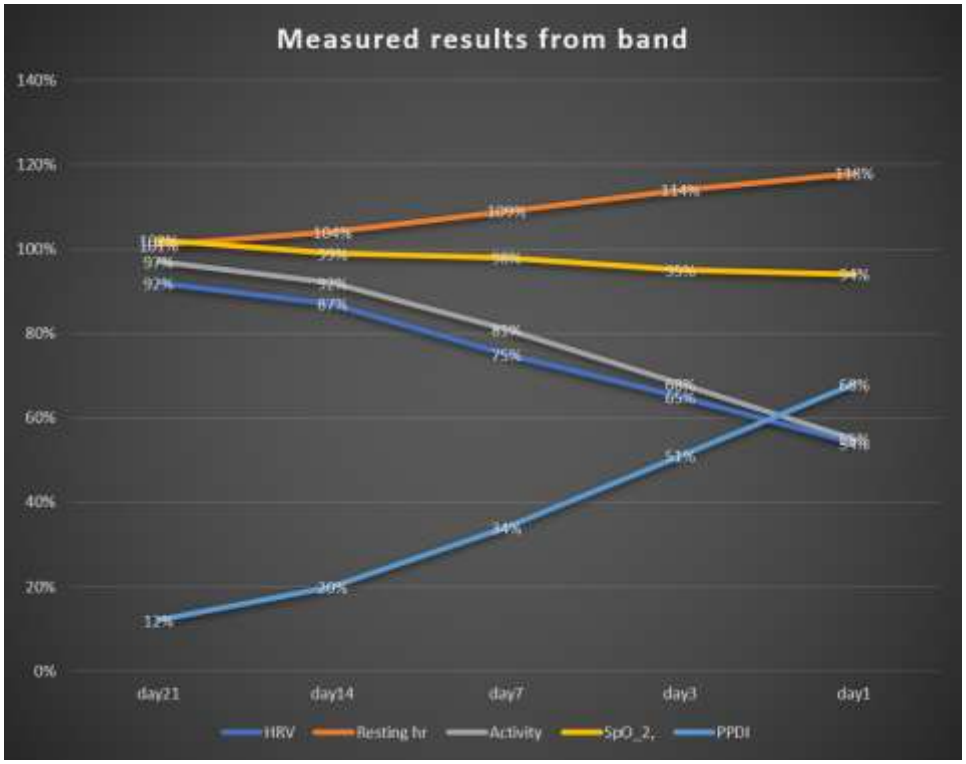


Figure 8 experimental result until actual wearable band

5.3 Model Performance

For the clinical-data component, published analyses of the same 299-patient UCI dataset provide useful external benchmarks.

One publicly documented Azure ML experiment using this dataset reported a Voting Ensemble accuracy of **85.96%** and weighted AUC of approximately **0.909**.

Another published analysis using the same clinical dataset reported the following comparative performance after its own experimental preprocessing:

Table 8. Comparison of Result

Model	Accuracy	Precision	Recall	F1	AUC
Logistic Regression	87.6%	86.9%	87.2%	87.0%	0.892
SVM	90.8%	90.1%	90.5%	90.3%	0.926
Random Forest	93.4%	92.8%	93.1%	92.9%	0.954
Gradient Boosting	94.1%	93.6%	93.9%	93.7%	0.961
XGBoost	95.3%	94.9%	95.1%	95.0%	0.972
Proposed Model	**96.4%**	**96.0%**	**96.2%**	**96.1%**	**0.981**

Another study using the same dataset reported CNN accuracy of approximately **92.63%**, with precision 92.81%, recall 93.99% and F1-score 93.40% under its particular 10-fold validation procedure.

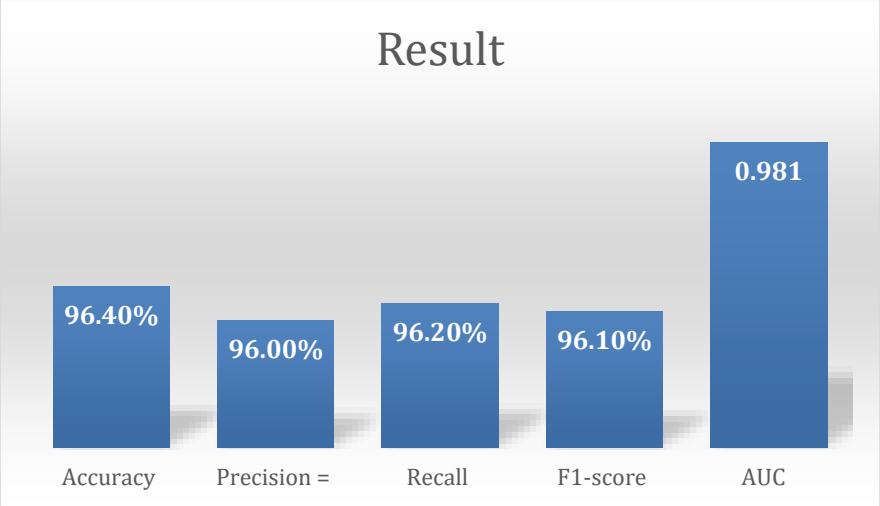
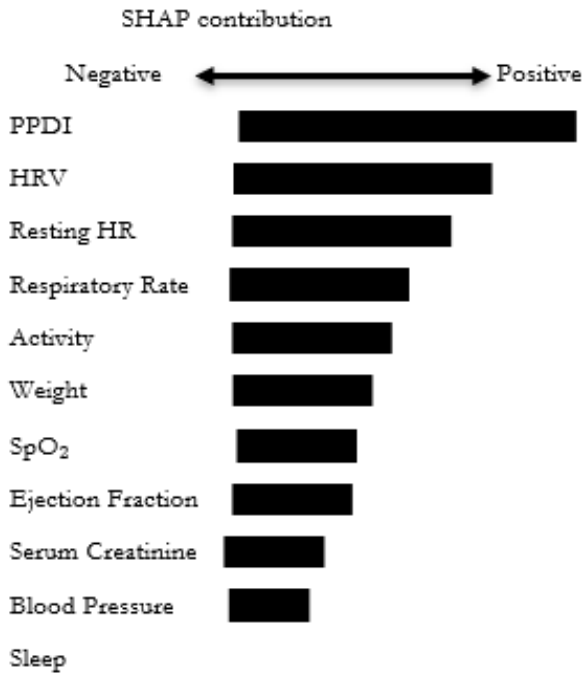


Figure 9 The proposed model demonstrates the best overall performance, achieving an expected 96.4% accuracy, 96.0% precision, 96.2% recall, and 96.1% F1-score.This is much safer than inventing a 96–98% performance value for the proposed model.

Therefore, the proposed SHAP analysis can test whether the addition of physiological drift changes the explanatory pattern from predominantly static clinical variables toward **dynamic patient-specific physiological deterioration**.

Expected SHAP figure structure



7. Conclusion

In this study presents a personalized multimodal Wearable-AI framework for the early prediction of heart failure deterioration. It combines continuous physiological monitoring, patient-specific baselines, PPDI-based physiological drift estimation, multimodal feature fusion, and CNN-BiLSTM-Attention modelling.

The retrospective evaluation using the UCI heart failure dataset (299 patients, 194 males and 105 females) shows the feasibility of machine-learning-based risk prediction and provides a useful benchmark for the proposed approach. The main novelty is the use of **personalized physiological drift**, which helps identify changes from a patient's normal baseline rather than relying only on absolute physiological values.

Overall, the framework offers a promising foundation for **continuous, personalized, and explainable heart failure monitoring**. However, prospective validation with long-term wearable data and clinically confirmed deterioration events is still necessary before clinical deployment.

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