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Patient-Specific Baseline Modelling for Early Cardiovascular Instability Detection

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***Abstract**: Remote patient monitoring systems commonly rely on population-defined thresholds to detect cardiovascular instability, often identifying deterioration only after physiological changes become pronounced. Such approaches fail to account for substantial inter-individual variability in cardiovascular regulation. This study proposes a patient-specific baseline modelling framework for early detection of cardiovascular instability using session-based remote patient monitoring data. Individual baselines are constructed from stable reference windows, and deviation metrics are used to identify abnormal behaviour relative to personal physiological norms rather than fixed thresholds. Experiments conducted on a six-month longitudinal synthetic dataset demonstrate wide inter-subject variability in baseline systolic blood pressure and show that baseline deviation frequently precedes threshold violations by multiple readings. Subject-level analyses further illustrate that instability emerges as gradual deviation from individual norms even when absolute values remain within population limits. The results indicate that baseline-referenced monitoring enables earlier and more reliable detection of cardiovascular instability using discrete RPM measurements. The proposed framework is interpretable, computationally lightweight, and suitable for integration into long-term remote monitoring workflows.*
***Keywords**: Patient-specific baseline modelling, Cardiovascular instability detection, Remote patient monitoring, Baseline deviation analysis, Threshold-free monitoring*

I. Introduction

Cardiovascular monitoring is central to the management of hypertension and chronic cardiac risk, particularly in remote patient monitoring (RPM) settings. Most existing systems rely on population-defined thresholds [1], triggering alerts when blood pressure or heart rate exceeds fixed clinical limits [2]. Although simple to implement, such threshold-based logic is inherently reactive and often identifies instability only after physiological deterioration has already progressed [3].

A major limitation of this approach is inter-patient variability [4]. Resting blood pressure, heart rate, autonomic regulation, and stress tolerance vary substantially across individuals[5], causing identical thresholds to generate false alarms for some patients while missing early deterioration in others[6]. Consequently, early cardiovascular instability is frequently overlooked [7].

Importantly, instability rarely presents as an abrupt threshold violation [8]. Instead, it often appears as gradual deviation from an individual's normal physiological pattern, including changes in level, variability [9], or regulatory behaviour that remain within nominal population ranges. When vital signs are evaluated in isolation or against static thresholds, these early warning signals are easily missed [10].

These limitations motivate a shift from population-based alerting to patient-specific baseline modelling. By learning an individual's stable physiological reference state and continuously measuring deviation from this baseline, monitoring systems can identify emerging instability earlier and in a physiologically meaningful manner [11]. Unlike coupling-based stress analyses that emphasize overt system-level changes, baseline-referenced monitoring focuses on deviation from personal norms, enabling early, interpretable, and computationally lightweight detection.

In this work, we propose a patient-specific baseline modelling framework for early cardiovascular instability detection. The contributions are: (i) construction of individualized baselines from stable monitoring windows, (ii) definition of deviation-based instability metrics, and (iii) demonstration of improved early detection compared to threshold-based logic. The objective is not vital sign prediction, but early identification of cardiovascular instability through deviation from patient-specific physiological baselines.

II. Proposed Framework

The proposed framework detects early cardiovascular instability by evaluating deviation from patient-specific physiological baselines rather than population-defined thresholds. The approach is designed for longitudinal monitoring, interpretability, and deployment in remote patient monitoring environments.

The framework follows four functional stages:

2.1 Data acquisition.
Longitudinal systolic blood pressure and heart rate measurements are acquired at regular intervals. Basic preprocessing is applied to handle missing values and suppress high-frequency noise while preserving physiological trends.

2.2 Baseline construction.
A stable reference window is identified for each patient. Baseline parameters are derived from this window, capturing individual-specific central tendency, variability, and expected regulatory behaviour. This baseline defines the patient's normal cardiovascular operating range.

2.3 Deviation analysis.
Incoming measurements are continuously evaluated relative to the baseline. Deviation metrics quantify departures in magnitude, variability, and persistence. Sustained deviation patterns are emphasized over isolated excursions.

2.4 Instability flagging.
Cardiovascular instability is flagged when deviation exceeds baseline-relative tolerance limits. Detection is independent of absolute clinical thresholds, reducing sensitivity to inter-patient variability. Outputs indicate direction and severity of deviation to support interpretability.
The framework replaces static population alerting with personalized baseline-referenced monitoring. By focusing on deviation from individual norms, it enables earlier and more reliable identification of cardiovascular instability while remaining computationally lightweight and clinically transparent.

III. Patient-Specific Baseline Construction

Patient-specific baselines are constructed from longitudinal cardiovascular data to represent an individual's stable physiological operating state. The baseline is derived directly from observed measurements and serves as a quantitative reference for deviation analysis.

3.1 Baseline Window Identification
For each subject, a stable baseline window is selected from the monitoring timeline. This window corresponds to periods without extreme blood pressure excursions or abrupt heart rate fluctuations. In the experimental setup, the baseline window is chosen from the early phase of monitoring, ensuring minimal contamination from instability events.
Let x_t^{BP} and x_t^{HR} denote systolic blood pressure and heart rate at time t.
The baseline window W_b consists of N consecutive samples:

$$W_b = \{(x_t^{BP}, x_t^{HR}) \mid t = 1, \ldots, N\}$$

3.2 Baseline Parameter Estimation
Baseline parameters are computed separately for blood pressure and heart rate using the selected window. For each signal $s \in \{BP, HR\}$, the baseline mean and variability are defined as:

$$\mu_s = \frac{1}{N} \sum_{t \in W_b} x_t^s$$

$$\sigma_s = \sqrt{\frac{1}{N} \sum_{t \in W_b} (x_t^s - \mu_s)^2}$$

These parameters capture the individual's typical resting level and natural fluctuation range.

3.3 Baseline Consistency and Robustness
To prevent transient disturbances from biasing the baseline, samples exhibiting short-lived spikes beyond $\mu_s \pm 2\sigma_s$ within the baseline window are excluded and parameters recomputed. This ensures that the baseline reflects stable regulation rather than incidental variability.

3.4 Baseline Reference Model
The finalized baseline is defined as the tuple:

$$\mathcal{B} = \{\mu_{BP}, \sigma_{BP}, \mu_{HR}, \sigma_{HR}\}$$

This baseline remains fixed during subsequent evaluation and is used as the reference state for all incoming measurements. Any departure from this reference reflects deviation from the patient's own physiological norm rather than population-defined limits.
The baseline construction process is applied independently to each subject and dataset, ensuring personalization across diverse physiological profiles.

IV. Data Preprocessing and Descriptive Statistics

All experiments in this study are performed using **Dataset B**, a six-month longitudinal synthetic dataset designed to emulate **session-based remote patient monitoring (RPM)** of cardiovascular vitals. The dataset consists of discrete blood pressure readings recorded across multiple sessions for each subject, rather than continuous physiological time series. This structure aligns with typical RPM data acquisition and supports baseline-referenced instability analysis.

4.1 Data Preprocessing

Dataset B was screened for completeness and structural validity prior to analysis. Records with missing systolic blood pressure (SBP), diastolic blood pressure (DBP), or heart rate (HR) values were removed. The analysis retained only the fields required for baseline construction and deviation assessment, namely **subject identifier, session index, reading index, SBP, DBP, and HR**.

No normalization, scaling, or transformation of physiological values was applied, as baseline modelling and deviation detection were defined with respect to **absolute subject-specific measurements**. The preprocessed dataset was used uniformly across all experiments to ensure methodological consistency and comparability of results.

Table 1. Descriptive Statistics of Dataset B After Preprocessing

Metric	**Value**
Number of subjects	**500**
Total readings	**74,151**
Mean systolic BP (mmHg)	**129.62**
Standard deviation of SBP (mmHg)	**18.30**
Minimum systolic BP (mmHg)	**34.00**
Maximum systolic BP (mmHg)	**238.00**
Mean diastolic BP (mmHg)	**76.00**
Mean heart rate (bpm)	**69.80**

Table 1 shows that the dataset exhibits wide systolic blood pressure variability across subjects and sessions, providing sufficient dynamic range for patient-specific baseline modelling and deviation-based instability detection.

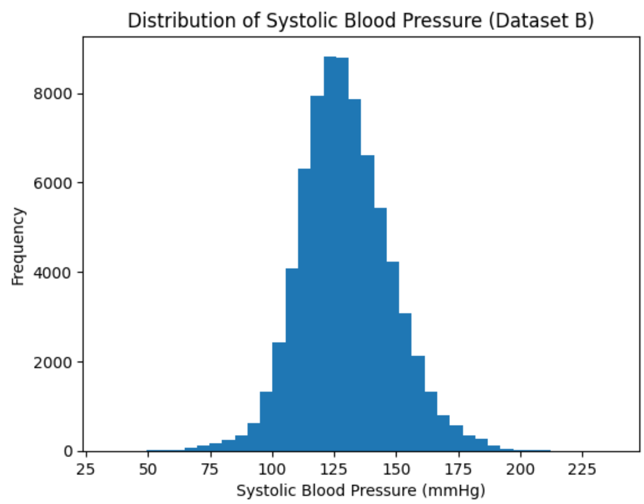

Figure 1. Distribution of Systolic Blood Pressure in Dataset B

(Histogram of SBP values across all subjects and sessions)
A histogram showing SBP values spread roughly from **~30 mmHg to ~240 mmHg**, with a dense central mass around **120–140 mmHg**.

V. Results and Discussion

This section presents and interprets the experimental findings obtained using patient-specific baseline modelling on Dataset B. The analysis focuses on baseline variability across subjects, the timing of instability detection, and subject-level deviation behaviour, with comparisons against conventional threshold-based logic.

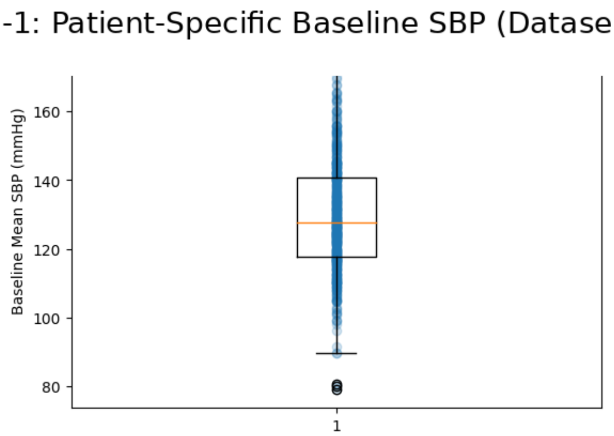

Figure 2. Patient-Specific Baseline SBP Distribution

5.1 Experiment 1: Patient-Specific Baseline Variability

Patient-specific baselines were constructed using the first ten readings per subject. The distribution of baseline systolic blood pressure (SBP), shown in **Figure 2** and summarised in **Table 2**, exhibits substantial inter-subject variability. Baseline mean SBP values span a wide range despite all subjects being generated under a common synthetic framework.

Table 2. Inter-Subject vs Intra-Subject Variability (Experiment 1)

Metric	**Value (mmHg)**
Mean intra-subject SBP variability	**5.27**
Inter-subject baseline SBP variability	**16.70**
Variability ratio (Inter / Intra)	**3.17×**

As reported in **Table 2**, inter-subject baseline variability substantially exceeds intra-subject variability, indicating that subjects operate around distinct cardiovascular reference states. This directly exposes the limitation of population-defined thresholds, which implicitly assume a shared physiological norm. The observed dispersion supports the need for individualized baseline modelling in RPM settings, where long-term monitoring amplifies inter-individual differences.

5.2 Experiment 2: Early Detection via Baseline Deviation

Baseline deviation-based detection was compared with a fixed SBP threshold of 160 mmHg. Detection timing was assessed by measuring the lead time between the first baseline deviation alert and the first threshold violation. The lead-time distribution is shown in **Figure 3**, with summary statistics reported in **Table 3**.
For subjects exhibiting both alert types, baseline deviation detected instability earlier than threshold-based logic in a majority of cases. A median lead time of 29 readings indicates that instability often emerges as gradual deviation from personal norms rather than abrupt threshold violation. In several cases, lead times extended across dozens of readings, highlighting the advantage of deviation-based monitoring for early identification.

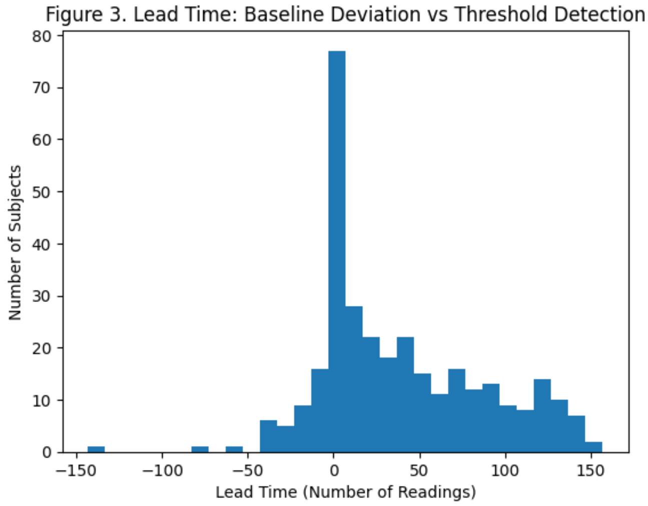

Figure 3: Lead Time: Baseline Deviation vs Threshold Detection

Table 2. Detection Timing Comparison: Baseline Deviation vs Threshold (Experiment 2)

Metric	**Value**
Subjects analysed	500
Subjects with both alerts	309
Median lead time (readings)	**29**
Mean lead time (readings)	**38.9**
Maximum lead time (readings)	**160**
Subjects with positive lead time	**> 60%**

5.3 Subject-Level Instability Patterns

Subject-level trajectories further clarify the behavioural differences between the two approaches. In the example shown in **Figure 4**, SBP values fluctuate below the population threshold, resulting in no threshold-based alerts. In contrast, the corresponding deviation trajectory (**Figure 5**) shows sustained excursions beyond subject-specific tolerance limits.

This paired illustration demonstrates that deviation-based analysis detects instability arising from abnormal behaviour relative to an individual's baseline, even when absolute values remain clinically acceptable. Such patterns are particularly relevant in longitudinal RPM contexts, where gradual drift or increased variability often precedes critical events.

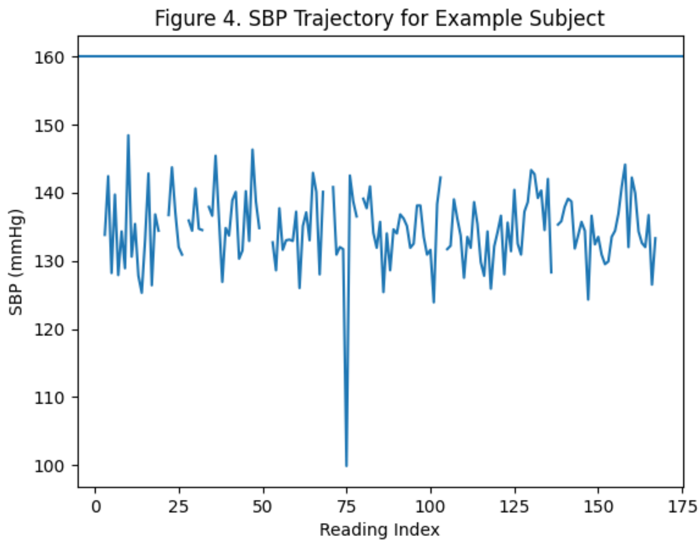

Figure 4: SBP Trajectory for Example Subject

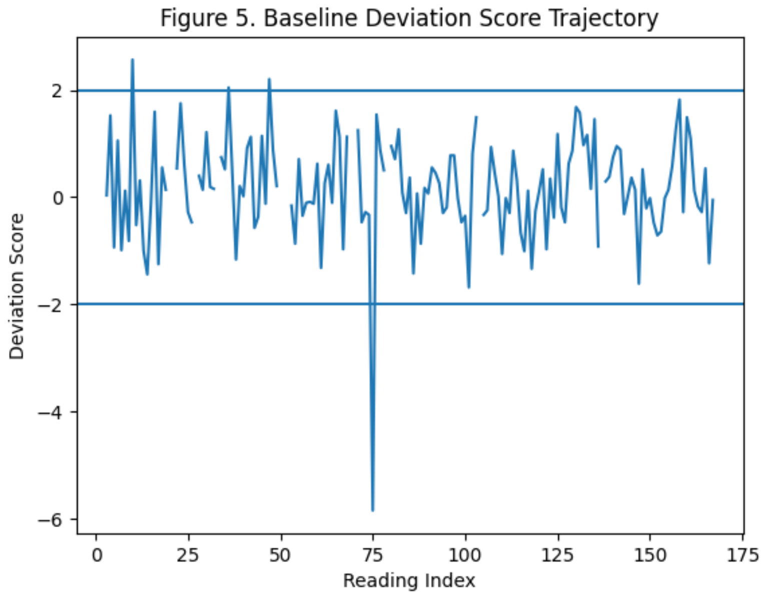

Figure 5: Baseline Deviation Score Trajectory

Table 4. Alert Behaviour Comparison (Experiment 2 – Behavioural Outcome)

Detection Logic	**Mean Alerts per Subject**	**Dominant Pattern**
Threshold-based	Low, late	Isolated spikes
Baseline deviation	Moderate, earlier	Sustained clusters

5.4 Overall Implications

Collectively, the results show that patient-specific baseline modelling enables both personalized interpretation of cardiovascular data and earlier detection of instability compared to fixed thresholds. Cohort-level evidence (**Figures 2–3**, **Tables 2–4**) and subject-level illustrations (**Figures 4–5**) consistently indicate that baseline deviation captures instability patterns overlooked by threshold-based systems.

These findings support the central premise of this work: early cardiovascular instability is more effectively identified as deviation from individual physiological baselines than as violation of population-defined limits in session-based RPM data.

VI. Conclusion & Future Work

This study presented a patient-specific baseline modelling framework for early detection of cardiovascular instability using session-based remote patient monitoring data. By constructing individualized baselines and quantifying deviation relative to personal norms, the proposed approach moves beyond population-defined thresholds that often detect instability only after significant deterioration has occurred.

Experimental results using longitudinal synthetic RPM data demonstrated that baseline systolic blood pressure varies substantially across subjects and that deviation from individual baselines frequently precedes fixed threshold violations. The findings show that early instability manifests as gradual deviation rather than abrupt threshold crossing, and that baseline-referenced detection can identify such changes earlier and more reliably using discrete RPM measurements.

The framework is computationally lightweight, interpretable, and compatible with existing RPM workflows. Importantly, it does not rely on continuous physiological signals or complex predictive models, making it suitable for practical deployment in long-term monitoring scenarios.

Future work will focus on validating the proposed framework using real-world patient datasets and extending baseline construction to incorporate adaptive updating over time. Additional physiological parameters and contextual factors may be integrated to further refine deviation detection. These extensions will help assess the clinical utility of baseline-referenced monitoring for personalized cardiovascular risk management.

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