Unsupervised Physiological State Differentiation and Anomaly Detection

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Abstract— **The article presents an analytical extension of our previously published study on HRV-based physiological state recognition using unsupervised learning. Building upon the original PCA + K-Means + DBSCAN framework, the current work focuses on a deeper interpretation of selected outcomes, particularly the interplay of fractal metrics (DFA α1/α2, Hurst exponent) and nonlinear entropy features in differentiating rest, stress, and physical load conditions. Additional analysis highlights the physiological relevance of borderline and anomaly cases identified by DBSCAN, suggesting early deviations in autonomic regulation. A comparison of the findings with recent HRV clustering studies is also made to highlight methodological advantages and limitations. The results reinforce the potential of label-free clustering for real-time monitoring and decision support in wearable health systems.**

***Keywords*—DBSCAN, HRV, K-Means, PCA.**

I. INTRODUCTION

Unsupervised machine learning techniques have gained increasing attention in recent years for their ability to extract structure and detect physiological states from Heart Rate Variability (HRV) data without requiring predefined labels. Prior studies have applied K-Means clustering to time- and frequency-domain HRV metrics to separate daily-life conditions such as rest, stress, and physical load, extending the approach to risk prediction using Gradient Boosting. In rehabilitation contexts, cluster analysis combined with Principal Component Analysis (PCA) has shown potential in identifying heterogeneous responders among patients with Parkinson's disease undergoing aerobic exercise. Wearable validation studies further demonstrated that HRV-derived parameters are sensitive to physiological differences related to fitness and body composition.

The present article serves as an analytical extension of our previously published work [1], in which a hybrid unsupervised framework—integrating PCA, K-Means, hierarchical clustering (Ward), and DBSCAN (Density-Based Spatial Clustering of Applications with Noise)—was used to distinguish physiological states and detect anomalies from combined linear, spectral, nonlinear, and fractal HRV features. The contribution of this extended analysis lies not in introducing a new model, but in re-examining key outcomes to better understand the latent structure of the data, the behavior of fractal and entropy metrics, and the physiological interpretation of borderline or atypical cases identified through density-based clustering. By contextualizing these findings within related literature, this study provides deeper insights into the utility and limitations of label-free HRV clustering for real-time monitoring and decision support in wearable health applications.

Related Works

Several recent studies have applied unsupervised learning approaches to HRV data to identify physiological states. In [2], K-Means clustering was applied to HRV features in the time and frequency domains to distinguish physiological states such as "rest", "stress" and "exertion" during daily activities, and Gradient Boosting was subsequently used to predict fall risk.

Assessing HRV in Parkinson's disease rehabilitation, a study [3] on 110 Parkinson's disease patients performed cluster analysis and PCA, identifying four different types of responders to aerobic exercise (vigorous, moderate, mixed and low responders).

Validation of the Polar H7 wearable device during physical activity [4] showed that the K-Means algorithm effectively classified participants according to fitness level and body composition. The results show that HRV parameters measured by the device are sensitive to physiological differences related to aerobic capacity and body composition.

Research Questions:

Q1. Which hidden patterns and relationships within HRV, entropy, and fractal descriptors can be revealed when these metrics are projected into a reduced latent feature space?

Q2. Are unsupervised machine learning methods capable of reliably distinguishing between different physiological states when no prior class labels are available?

Q3. How effectively can AI-driven visual interpretation tools (e.g., PCA plots, heatmaps, cluster maps) assist in identifying atypical responses, natural subgroups, and borderline cases within HRV datasets?

II. Methods

This study utilizes the same dataset, protocol, and HRV feature extraction pipeline presented in our previous work [1] on unsupervised physiological state recognition. HRV signals were recorded in three controlled conditions—rest, psychological stress, and physical load—and preprocessed through digital filtering and hybrid R-peak detection to derive time-domain, spectral, nonlinear, and fractal descriptors. The feature set included SDNN, RMSSD, LF/HF ratio, sample entropy, Hurst exponent, fractal dimension, and DFA $\alpha 1/\alpha 2$.

Dimensionality reduction was performed using Principal Component Analysis to reveal latent axes of variation. K-Means clustering ($k = 3$), hierarchical clustering (Ward), and DBSCAN were applied to evaluate complementary grouping behavior and anomaly detection. Unlike the original study, which focused on methodological development, the present work concentrates on reexamining these results—comparing the contributions of fractal and entropy metrics, analyzing borderline classifications, and contextualizing the observed patterns with recent HRV clustering literature.

A total of 22 healthy male athletes participated in the study [1], with HRV signals recorded in three physiological conditions—rest, psychological stress, and physical load—resulting in three recordings per participant.

III. Rezults

How the techniques used contribute to answering the research questions of the study (Table 1):

Fractal metrics (DFA $\alpha 1$, $\alpha 2$, Hurst exponent, fractal dimension) provide a robust and theoretically sound framework for capturing the self-similarity, scaling, and complexity of physiological time series. These features go beyond the capabilities of linear HRV parameters and are sensitive to long-term correlations and the degree of autonomic flexibility. Their use allowed us to uncover latent regulatory dynamics that are not visible in classical time- or frequency-domain analysis – effectively supporting the discovery of hidden structures in HRV data (Research Question 1).

Unsupervised machine learning algorithms (K-Means, DBSCAN, hierarchical clustering) offer several key advantages:

• They operate on unlabeled data, which is consistent with real biomedical settings where ground-truth annotation is often not available.

• K-Means provided efficient baseline clustering for the hypothetical three states (rest, stress, exercise).

• DBSCAN handled noise and outliers robustly, revealing transient and anomalous cases (e.g., participants in borderline physiological states).

• External validation metrics (Purity = 0.933, ARI = 0.89, NMI = 0.92) [1] indicate that the quality of the clustering is not only internally consistent, but also compatible with ex-pert-based physiological classifications (Research Question 2).

The AI-based visualizations (PCA biplots, heatmaps, clustermaps, and DBSCAN scatter plots) were instrumental in:

• Providing intuitive interpretation of high-dimensional HRV data.

• Revealing natural groupings in a reduced space.

• Highlighting the contribution of features to the principal components, which helps to understand the physiological basis of each cluster.

• Visual identification of anomalies, especially with DBSCAN, where noise points marked with an "X" indicate participants with potentially atypical autonomic profiles (Research Question 3).

Table 1. Strengths of the applied methods in relation to the research questions.

Method	*Research Question Addressed*	*Key Strengths*
Fractal Metrics (e.g., DFA α1/α2, Hurst exponent, Fractal Dimension)	Q1.	Capture long-range correlations, self-similarity, and complexity not visible in linear HRV measures.
K-Means Clustering		Simple, interpretable clustering into 3 states (Rest, Stress, Load); good baseline structure detection.
Hierarchical Clustering (Ward linkage)	Q2.	Provides nested structure and interpretability; confirms cluster separation aligned with physiological states.
PCA Biplots	Q1 & Q3.	Reveals major variance directions; links physiological features to clustering axes.
Heatmaps and Clustermaps	Q3.	Enable visual assessment of inter-individual similarity and distinct group profiles; identify hidden subgroups.
DBSCAN	Q2 & Q3.	Handles noise and outliers robustly; detects borderline cases and non-standard physiological profiles.

PCA revealed a dominant axis (PC1 ≈ 66%) that aggregates vagal-related indices (RMSSD, SDNN, Mean RR), while entropy and fractal metrics (SampEn, Hurst, DFA) articulate secondary axes that separate psychological stress from physical load. This indicates that combining magnitude (variability) and structural (complexity/fractality) descriptors provides complementary information for physiological state recognition. DBSCAN's isolation of borderline cases (detected outliers) illustrates the approach's potential for personalized early-warning in wearable systems

The PCA cluster analysis identified outliers that revealed deviations from the dominant physiological patterns in each condition. One participant from the Rest cluster was positioned at PC1 = –0.45, significantly higher than the typical Rest range (PC1 = –2.3 to –2.0), placing it closer to the stress centroid. This suggests possible increased sympathetic activation despite a nominal resting state. Another participant from the Load cluster showed PC1 = –0.10 and PC2 = –0.60, deviating from the typical Load position (> 0.3 in PC1 and < –1.5 in PC2) and aligning more closely with the Rest profile.

A comparison in terms of methodology, data types and clustering techniques of several articles with the present study is presented in Table 2.

Table 2. Methodology, data types, and clustering techniques.

Study	*Methodology*	*Data*	*Clustering Technique*
Ref. [2]	HRV-based stress detection and fall risk monitoring during daily activities; supervised ML models	Wearable HRV recordings during daily activities	K-Means
Ref. [3]	HRV as a biomarker for autonomic function in Parkinson's rehabilitation; exercise-induced changes	HRV during rehabilitation exercises	hierarchical clustering
Ref. [5]	Unsupervised identification of mental stress in firefighters using deep learning	HRV from firefighters under stress tasks	deep clustering (autoencoder-based)
Ref. [6]	Stratifying autonomic nervous system regulation patterns in healthy men	HRV from healthy men at rest	K-Means
Current study	HRV-based classification across rest, stress, and load using multimodal analysis	Experimental HRV dataset (N=22) in 3 conditions	Combination of clustering methods: K-Means, hierarchical, and DBSCAN

In contrast to the referenced studies, which often adopt a single clustering approach (e.g., K-Means in Messaoud et al. [2], hierarchical clustering in Basri et al. [3], or a deep learning pipeline without comparative unsupervised baselines in Oskooei et al. [5]), the present work leverages a multi-algorithmic clustering framework combining K-Means, hierarchical clustering, and DBSCAN. This diversification mitigates the method-specific sensitivity and instability seen in single-technique designs, enabling cross-method validation of the derived clusters. Moreover, while several prior works limit their feature sets to conventional time-domain and frequency-domain HRV indices, our methodology extends the feature space with nonlinear and fractal descriptors (SampEn, DFA α1, DFA α2, Hurst exponent), thus capturing subtler autonomic regulation patterns that traditional metrics fail to detect. The resulting clusters are therefore not only algorithmically more robust but also physiologically richer.

Justification of the PCA + K-Means + DBSCAN Framework

The combined use of Principal Component Analysis (PCA), K-Means, and DBSCAN offers several methodological advantages for unsupervised exploration of HRV data:

Dimensionality reduction via PCA allows the projection of heterogeneous HRV features (linear, spectral, nonlinear, and fractal) into a compact orthogonal space. This mitigates multicollinearity, improves computational efficiency, and highlights latent axes of physiological variation.

K-Means clustering is well-suited for discovering spherical and balanced group structures in the principal component space, providing a fast and interpretable baseline for group separation based on central tendencies.

DBSCAN complements this by identifying arbitrary-shaped clusters and outliers, which K-Means cannot capture. It is particularly effective for detecting transitional or rare physiological states, including those not represented in the majority of the population.

When combined, PCA simplifies the input space, K-Means uncovers global groupings, and DBSCAN identifies local density anomalies. When combined, PCA simplifies the input space, K-Means uncovers global groupings, and DBSCAN identifies local density anomalies.

In this study, PCA and DBSCAN complemented each other particularly well. PCA reduced the dimensionality of the HRV feature set to the first two principal components, which explained over 70% of the variance, enabling clear visual separation between Rest, Stress, and Load states while preserving the key physiological differences. DBSCAN then operated directly on these reduced coordinates to form clusters based on point density and identify anomalies (Cluster = –1). While PCA provided an intuitive visualization of grouping tendencies, DBSCAN quantitatively defined membership and automatically isolated atypical cases—such as participants with mixed autonomic responses—labeling them as “noise.” This dual approach yielded consistent overall cluster structures, with DBSCAN excelling in the detection of boundary and atypical profiles, and PCA offering a clearer interpretation of global inter-state relationships. This synergy enables both robust clustering and unsupervised anomaly detection in HRV monitoring.

Although the sample size is limited, it reflects a relatively homogeneous group of experienced combat sports athletes, allowing for a focused assessment of HRV dynamics under intense physical and psychological conditions. Participant variability was con-trolled by selecting only healthy men with regular training regimens (5 days per week for 2 hours), minimizing confounding factors such as age-related cardiovascular variations or comorbidities. The dataset included balanced recordings in three different physiological states—rest, exercise, and stress—collected under standardized training and competition conditions. The sensitivity of the model to clustering parameters was assessed by varying ε and minPts in DBSCAN, and the robustness was confirmed in several configurations (see Section 3.5).

Table 3 presents an analysis of similar studies on a number of parameters.

Table 3. Comparative Analysis of Related HRV-Based Studies and the Proposed Approach

Parameter	Ref. [2]	Ref. [3]	Ref. [6]	Ref. [5]	Current Study
Domain/ Application	HRV for stress and fall risk	HRV in Parkinson’s disease	Autonomic regulation in healthy males	Psychological stress in firefighters	Recognition: rest, stress, workload
Data type	HRV (time/frequency)	HRV (pre-/post-activity)	HRV	HRV	HRV (including nonlinear indicators)

Feature diversity	Medium	Moderate (low–medium)	Medium	Medium	High
Methodology	Supervised ML (with labels)	K-Means clustering	Clustering/ classification	Autoencoder + clustering	PCA + K-Means + DBSCAN (hybrid)
Computational complexity	Medium–high	Low	Medium	High	Medium
Requires labels	No	Partial	Partial	Yes	Yes
Anomaly detection	Limited	Yes	Moderate	Strong	Strong
Interpretability	Moderate	High	Moderate	Low	High
Main limitations	Requires labels and large datasets	Specific to clinical scenario	Limited to healthy males	Risk of overfitting	Requires fine-tuning in noisy data
Advantages of our approach	Fully label-free; robust to noise and incomplete data	Multi-component; applicable in different contexts	Works with diverse populations	Clear and easy to implement	A combination of visualization, clustering, and anomaly detection

Messaoud & Thamsuwan (2025) [2] study applied K-Means clustering to HRV features and showed stress-induced reductions in RMSSD and increases in LF/HF ratio, although they did not provide exact numerical values. Similarly, Basri & Turki (2025) [3] observed significant HRV changes in Parkinson's patients following aerobic activity, with post-exercise increases in vagal tone reflected by LF/HF normalization. In contrast to these qualitative results, our study provides a full quantitative differentiation between the three physiological states. For example, RMSSD decreases from 28.39 ± 7.24 ms (Rest) to 9.86 ± 4.81 ms (Stress) and partially recovers during Physical Load (18.22 ± 5.93 ms). Similarly, LF/HF ratio rises markedly from 0.59 ± 0.11 (Rest) to 2.12 ± 0.23 (Stress), and then decreases to 1.22 ± 0.14 (Load), reflecting sympathetic–parasympathetic shifts consistent with mental and physical burden. DFA analysis further confirms these transitions, with α1 dropping from 1.14 ± 0.06 (Rest) to 0.88 ± 0.08 (Stress), then rising to 1.04 ± 0.07 (Load), and α2 showing a similar trend: $1.33 \pm 0.05 \rightarrow 0.86 \pm 0.07 \rightarrow 0.99 \pm 0.06$, which aligns well with known autonomic modulation patterns.

Zamora-Justo et al. (2025) [7] reported that participants with metabolic syndrome exhibit significantly lower DFA and SampEn values (no specific numerical values) both at rest and during exercise compared to healthy controls, indicating reduced autonomic complexity in MetS—even though specific numeric values for DFA α1/α2 descriptors were not provided. This qualitative alignment further supports our findings, which show a pronounced reduction in DFA α1 (from 1.14 at rest to 0.88 under stress), with intermediate values under physical load (1.04), illustrating how DFA metrics reliably reflect different physiological stress states.

Materko [6] investigates autonomic nervous regulation in healthy men through machine learning using a limited set of HRV metrics (mainly linear time and frequency parameters). Classification and clustering were applied in a relatively homogeneous population and without emphasis on visualization of latent structure. In contrast, we use a more diverse set of metrics (including nonlinear and fractal), apply PCA and hybrid clustering (K-Means + DBSCAN) to recognize different physiological states in heterogeneous data.

Borthakur et al. (2018) [8] work with multimodal smartwatch signals and use K-Means, GMM and SOM to detect natural groups in the data. Although the method is completely label-free, the visualizations are limited to basic scatter plots and are not inte-grated with the interpretation of physiological indicators. Our study extends the approach by combining PCA and DBSCAN/K-Means, providing richer visualization (2D/3D PCA, heatmap, clustermap), and includes nonlinear HRV indices for deeper physiological interpretation.

Schrumpf et al. (2017) [9] apply hierarchical clustering on physiological parameters during exercise, demonstrating agreement with experimental phases. However, their approach has fixed metrics and is less robust to noise. Our work also achieves real-world match, but with a hybrid algorithm and adaptive settings, robust to noise and incomplete data, making it applicable to real-world "in-the-field" measurements.

Serantoni et al. (2022) [10] use clustering to dynamically track fatigue in running, linking HR patterns to VO_2max and the onset of fatigue. The method is highly effective, but focused in a specific sports context. Our study applies similar label-free clustering, but in a broader context – recognizing rest, stress, and exercise under a variety of conditions, with higher feature diversity and integrated anomaly detectors.

In the study by Oskooei et al. (2019) [5], a clustering approach on latent representations extracted by autoencoders was used to distinguish two psychophysiological clusters among firefighters participating in a training session. It is important to note that all participants were in an active, busy state – i.e., no resting control condition was included. However, the authors distinguished individuals with a normal parasympathetic response (high RMSSD, low LF/HF ratio) from those with manifest mental stress. In contrast, the present study uses real and clearly distinguished physiological states – rest, mental stress, and physical exertion – and offers an extended set of features, including fractal and entropic metrics. This provides a broader range of assessment and more interpretable behavior of the clustering algorithms. The comparison highlights the complementary nature of the approaches, with the present study emphasizing real-time biomedical applicability and interpretability of the indicators.

Limitations

The present study has several limitations that should be acknowledged.

First, the number of participants and recordings was relatively small, which con-strains the statistical power and generalizability of the findings. Although the dataset was balanced across three physiological states (rest, exercise, and stress) and collected under standardized conditions, the limited sample size means that the clustering patterns observed—while consistent—should be interpreted with caution.

Second, the participants represented a relatively homogeneous group of experienced combat sports athletes. This reduces variability from confounding factors such as age, sex, and comorbidities, but it also limits the applicability of the results to other populations, including sedentary individuals, women, or athletes from other sports.

Third, the HRV features used were extracted from short-term recordings under con-trolled conditions; further research should examine the robustness of the proposed PCA + K-Means + DBSCAN framework using long-term monitoring data, real-world environments, and larger, more heterogeneous cohorts.

Future Work

In the validation study [3], physical activity included aerobic and submaximal endurance exercise, which are representative of moderate daily activity and training load. In our future work, we will aim to extend these observations by applying clustering and dimensionality reduction techniques to HRV data collected during typical daily activities such as walking, standing, sedentary work, and light exercise, which reflect common physiological states encountered in real-world monitoring scenarios. This will support the applicability of the proposed framework in both fitness and general health contexts.

The study in [4] demonstrated that HRV analysis with PCA and clustering can reveal different responses to interventions, even in chronic conditions. This confirms the applicability of nonlinear and fractal features, as well as unsupervised clustering, in clinical scenarios. In future work, we plan to adapt our framework to assess rehabilitation effects, chronic stress or cognitive load, as well as to monitor patients with cardiac diseases who need health monitoring, including post-stroke conditions. This would require longer time series, customized anomaly algorithms and adaptive learning models, but we expect the proposed architecture to be portable and effective in such cases.

Future comparison with supervised algorithms (e.g. SVM, Random Forest, DNN) and performance metrics (e.g. F1-score, ARI, silhouette) would strengthen the value of the results.

In future research, we plan to integrate the developed approach for automatic differentiation of physiological states and detection of deviations in real time into an existing wearable device for registration and monitoring of cardiac signals. The device was created within the framework of a current research project and includes PPG/ECG sensors, a wireless communication module, and multiplatform monitoring software.

IV. Conclusion

This analytical extension provides a deeper interpretation of previously obtained results on unsupervised HRV-based physiological state recognition. The findings reaffirm the value of combining fractal and entropy metrics with dimensionality reduction and clustering techniques to reveal latent autonomic dynamics and differentiate physiological states. The examination of borderline and anomaly cases highlights the potential for early recognition of atypical autonomic responses in real-time monitoring contexts. Overall, this complementary analysis strengthens the evidence for the applicability of label-free clustering in wearable health systems and supports future integration into personalized feedback and decision-support platforms.

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