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Observational Clinical Studies

Dynamic ECG Complexity in Atrial Fibrillation and Flutter: Cardiac Rehabilitation Monitoring and Functional Assessment

Ana-Maria Trofin [1], Dan Gheorghe Dimitriu [2], Vlad Ghizdovat [3,*], Dragos Ioan Rusu [4], Cati-Raluca Stolniceanu [3], Wael Jalloul [3], Alexandra-Iuliana Ungureanu [3], Andra Pintilie [5,*], Monica Molcalut [2] and Irena-Cristina Grierosu [3]

1 "Grigore T. Popa" University of Medicine and Pharmacy Iasi, Department of Surgery, Faculty of Medicine, Iasi 700115, Romania; "Alexandru Ioan Cuza" University, Faculty of Physics, Iasi 700506, Romania;
2 "Alexandru Ioan Cuza" University, Faculty of Physics, Iasi 700506, Romania;
3 "Grigore T. Popa" University of Medicine and Pharmacy Iasi, Department of Biophysics and Medical Physics, Faculty of Medicine, Iasi 700115, Romania;
4 "Vasile Alecsandri" University of Bacau, Department of Environmental Engineering, Mechanical Engineering and Agritourism, Faculty of Engineering, 600115 Bacau, Romania;
5 "Carol Davila" University of Medicine and Pharmacy Bucharest, Doctoral School, Department of Rehabilitation Medicine, 37 Dionisie Lupu Street, area 2, Bucharest, 4192910

* Correspondence: vlad.ghizdovat@umfiasi.ro; andra.pintilie@gmail.com

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Abstract: Atrial fibrillation (AF) and atrial flutter (AFL) are complex rhythm disturbances in which conventional electrocardiographic interpretation may not fully capture beat-to-beat dynamical organization. Quantitative ECG complexity may be relevant to future cardiac rehabilitation monitoring, but its clinical role remains unvalidated. This retrospective computational study analyzed annotated PhysioNet ECG/RR-interval recordings representing sinus rhythm, AF, AFL, and ectopic-dominated patterns. Linear heart-rate variability (HRV), entropy, fractal and multifractal indices, phase-space reconstruction, and recurrence quantification analysis were calculated. Synthetic RR series, when used, were restricted to algorithm checking and illustrative visualization and were not pooled with real-data summaries. In the selected segments, AF showed greater RR dispersion and entropy with reduced determinism, whereas AFL showed a shorter mean RR interval, higher fractal dimension, and partially organized cyclic attractor geometry. pNN50 was interpreted only after the stated NN-filtering procedure. Fractal dimension and entropy are candidate research descriptors of rhythm instability, not validated clinical thresholds. Prospective studies integrating wearable ECG, exercise-tolerance measures, patient-reported outcomes, and safety endpoints are required before these metrics can be considered for rehabilitation monitoring.

Keywords: atrial fibrillation; atrial flutter; fractal dimension; ECG; nonlinear dynamics; rehabilitation biomarkers

1. Introduction

Electrocardiography remains central to cardiovascular assessment because it directly records cardiac electrical activity. Conventional interpretation emphasizes waveform morphology, rhythm regularity, and summary rate measures; however, these descriptors may not fully capture the nonlinear temporal organization of beat-to-beat dynamics [1,2].

From a systems perspective, cardiac rhythm emerges from interactions among ion-channel kinetics, conduction pathways, autonomic modulation, and the structural substrate [3-5]. ECG waveforms and RR-interval series can therefore be examined as

outputs of a nonlinear dynamical system in which present beats are influenced by prior states and long-range correlations.

Nonlinear methods, including entropy analysis, fractal dimension, phase-space reconstruction, and recurrence quantification, have been applied to ECG signals to characterize organization not captured by classical linear HRV analysis alone [6,7].

AF and AFL are usually distinguished on surface ECG by morphology: AF is characterized by absent organized P waves and irregular ventricular intervals, whereas typical AFL commonly shows organized flutter waves and a macro-re-entrant atrial circuit [8-10]. These diagnostic categories remain the clinical standard; dynamical analysis may provide complementary quantitative descriptions of rhythm organization.

To better illustrate the electrophysiological differences between normal conduction and atrial fibrillation, a schematic representation is provided.

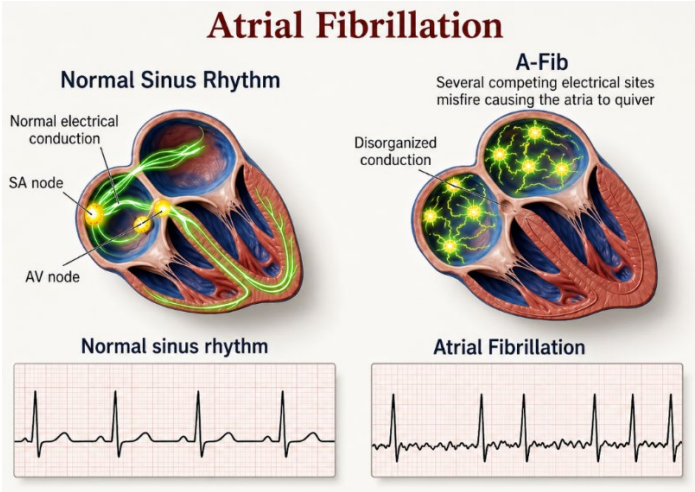

Figure 1. Electrophysiological mechanisms underlying sinus rhythm and atrial fibrillation.

The left panel of Figure 1 shows organized sinus conduction from the sinoatrial node to the atrioventricular node. The right panel illustrates AF as disorganized atrial activation driven by multiple electrical sources. The figure is used to orient the reader to the electrophysiological contrast rather than as a primary data source.

Cardiac rhythm may also be studied as a continuum of dynamical states rather than only as discrete diagnostic categories. Changes in RR variability, temporal coherence, and attractor geometry may accompany arrhythmic episodes, providing a rationale for quantitative complexity analysis [2,5].

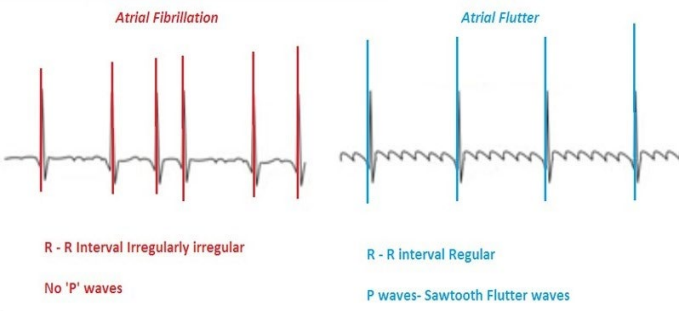

Figure 2. Electrocardiographic comparison between atrial fibrillation and atrial flutter.

Figure 2 summarizes the surface ECG distinction between AF and AFL. In the present study, these morphological labels were used as the rhythm categories against which nonlinear descriptors were compared.

Fractal and entropy-based measures provide complementary views of rhythm organization. Entropy estimates irregularity and unpredictability; fractal dimension, multifractal indices, and the Hurst exponent describe scaling behavior and long-range correlations; and phase-space and recurrence analyses describe attractor geometry and temporal structure [5-7,11-15].

The clinical translation of these metrics remains uncertain. Any proposed rehabilitation application must distinguish observed ECG findings from simulated or illustrative data and must not treat unvalidated fractal-dimension (FD) ranges as clinical decision thresholds [8,9].

The hypothesis of this study was that annotated rhythm states (sinus rhythm, AF, AFL, and ectopic-dominated segments) would show reproducible differences in HRV, entropy, fractal/multifractal, and recurrence-based descriptors, with AF showing greater dispersion and entropy and AFL showing a more organized but high-complexity pattern.

The aim was to build a transparent computational framework for characterizing ECG complexity in AF and AFL by integrating classical HRV metrics, entropy, fractal and multifractal descriptors, recurrence topology, and attractor geometry.

The contribution of this work is methodological: it integrates multiple nonlinear descriptors into a unified analysis and frames ECG complexity as a candidate research feature for functional monitoring. Rehabilitation applications are presented as future research directions requiring prospective validation, not as validated treatment rules [8,9].

2. Materials and Methods

This study was designed as a retrospective computational analysis of annotated ECG and RR-interval data. The primary hypothesis was that sinus rhythm, AF, AFL, and ectopic-dominated segments differ in nonlinear complexity metrics, including entropy, fractal dimension, multifractal spectrum width, and recurrence quantification indices.

The analytical framework was structured on three interconnected levels:

1. Signal level – ECG waveform and RR interval extraction
2. Statistical level – HRV metrics and distribution analysis
3. Dynamical level – nonlinear, fractal, and recurrence-based metrics

This multiscale architecture was intended to characterize cardiac rhythm beyond conventional descriptors [3-7,11-15].

2.1. Data sources and record selection

ECG and RR-interval data were extracted from public PhysioNet repositories with expert annotations [16,17].

ECG segments were selected from the public PhysioNet databases using the original rhythm annotations and were analyzed only within the time windows listed below. AFDB rhythm labels were retained as annotated, namely AFIB, AFL and N; the MITDB ectopy segment was included for visualization only. RR-interval counts refer to intervals retained after preprocessing, beat-quality review and NN filtering, where applicable. This is shown in Table 1.

Table 1. Record-selection log used for reproducibility of the computational analysis.

Database abbreviations: NSRDB = MIT-BIH Normal Sinus Rhythm Database; AFDB = MIT-BIH Atrial Fibrillation Database; MITDB = MIT-BIH Arrhythmia Database.

Database	Record / channel / fs	Rhythm label	Window	Duration	RR intervals	Exclusion / QC criteria	Use
NSRDB	16265 / ECG1 / 128 Hz	Sinus rhythm	00:00:30-00:05:30	300 s	294	Clean annotated segment; missing or implausible RR intervals excluded.	Primary baseline
AFDB	04015 / ECG1 / 250 Hz	AFIB (Episode 1)	00:06:55-00:07:50	55 s	71	Annotated AFIB interval; ectopic, noisy or non-analyzable beats excluded before NN metrics.	Primary AF
AFDB	08378 / ECG1 / 250 Hz	AFL	00:41:30-00:42:30	60 s	115	Annotated AFL interval; flat blocks, missing annotations and unstable signal edges excluded.	Primary AFL
AFDB	04015 / ECG1 / 250 Hz	AFIB (Episode 2)	00:08:55-00:10:55	120 s	141	Annotated second AFIB interval; same filtering rules as Episode 1.	Primary AF / reproducibility
AFDB	04015 / ECG1 / 250 Hz	N (post-event)	00:11:10-00:12:10	60 s	58	Post-AF annotated non-AF interval; no missing annotations in retained window.	Primary post-event
MITDB	207 / MLII / 360 Hz	Ectopic-dominated	00:28:10-00:29:10	60 s	70	Multiform PVC and ventricular-flutter/SVTA; noisy transition beats excluded.	Visualization only

Note. The ectopic-dominated MITDB segment was not pooled with AF/AFL/normal rhythm summaries; it was retained only to verify whether the visualization pipeline produced physiologically plausible attractor geometries in the presence of multiform ventricular ectopy.

Segments were eligible when annotated R peaks were available and when the segment represented one of the prespecified rhythm categories: sinus rhythm, AF, AFL, or ectopic-dominated rhythm. Segments with severe noise, missing annotations, or insufficient RR intervals for nonlinear analysis were excluded.

2.2. Signal preprocessing and RR-interval extraction

Signal preprocessing was performed to ensure robustness of downstream nonlinear analysis:

- Bandpass filter: 0.5–40 Hz
- Removal of baseline wander and high-frequency noise

R-peaks were identified using a modified Pan-Tompkins algorithm [18], based on:

$$y(n) = \frac{1}{8}[2x(n) + x(n-1) - x(n-3) - 2x(n-4)] \quad (1)$$

After differentiation, squaring, and moving-window integration, the detected peaks were visually validated against the ECG traces.

The RR interval series was defined as:

$$RR_i = t_{i+1} - t_i \quad (2)$$

where t_i represents the timestamp of the i-th R peak.

From RR intervals, the instantaneous heart rate was computed:

$$HR_i = \frac{60}{RR_i} \quad (3)$$

Synthetic RR series were not pooled with real PhysioNet observations for the primary HRV, entropy, fractal, multifractal, or recurrence summaries. When generated, synthetic series were used only for algorithm checking and illustrative attractor visualization under controlled constraints (mean heart rate preservation, variance matching, and optional ectopic patterns such as PVC/APC).

Accordingly, all primary numerical results should be interpreted as real-data descriptors; any simulated or synthetic figure is explicitly labeled as illustrative and hypothesis-generating.

2.3. Linear HRV and entropy analysis

Standard HRV metrics were computed as baseline descriptors:

- Mean RR interval
- SDNN (standard deviation of NN intervals)
- RMSSD (root mean square of successive differences)
- pNN50 (percentage of successive filtered NN-interval differences >50 ms; interpreted with caution in AF/AFL because strict NN filtering can suppress raw RR irregularity)

Mathematically:

$$SDNN = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(RR_i - \overline{RR}\right)^2}$$
$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N-1}(RR_{i+1} - RR_i)^2} \quad (4)$$

These metrics provided a linear reference for comparison with the nonlinear indices [1].

To quantify signal irregularity and information content, Shannon entropy and sample entropy were computed [7,11]:

$$H = -\sum\ p(x)\log\ p(x) \quad (5)$$

Defined as:

$$\text{SampEn}(m, r, N) = -\ln\left(\frac{A}{B}\right) \quad (6)$$

where:

- m = embedding dimension
- r = tolerance
- A, B = matched patterns

Higher entropy values were interpreted as greater irregularity and reduced predictability; this interpretation was descriptive and rhythm-segment specific.

2.4. Nonlinear, fractal, recurrence, and wavelet analysis

Fractal-dimension estimation used image-based and signal-based approaches. Figure 3 summarizes the fractal-analysis workflow.

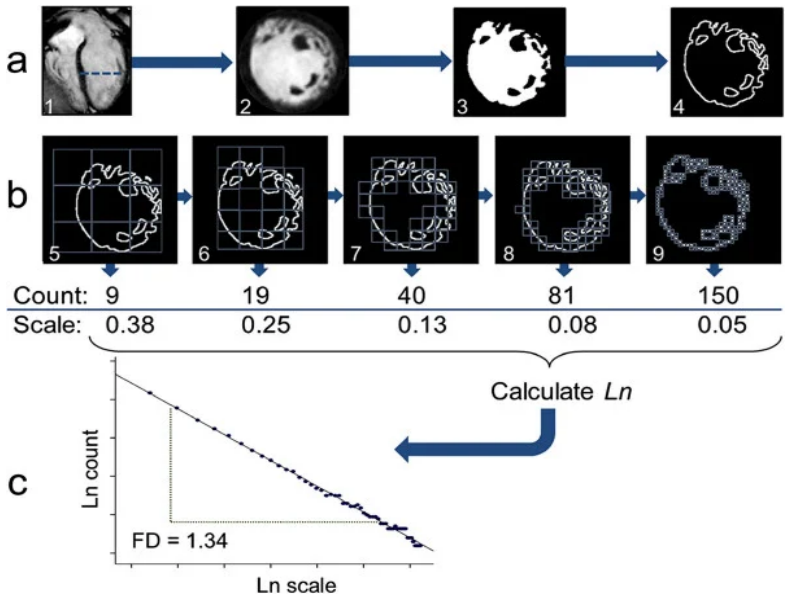

Figure 3. Fractal analysis workflow and myocardial structural complexity: (a) Myocardial trabecular structure; (b) anatomical segmentation; (c) edge detection and box-counting procedure utilized for fractal dimension estimation.

This workflow illustrates the quantification of structural and functional complexity using fractal metrics [19,20].

The Hurst exponent was estimated using detrended fluctuation analysis (DFA) [21]:

$$F(n) \sim n^H$$

Interpretation:

- $H > 0.5$: persistent correlations
- $H < 0.5$: anti-persistence

Fractal dimension was computed using multiple approaches:

(a) Higuchi method

$$FD_H = \frac{\log(L(k))}{\log(1/k)} \quad (7)$$

(b) Katz method

$$FD_K = \frac{\log(n)}{\log(d/L)} \quad (8)$$

(c) Relation with Hurst exponent

$$FD = 2 - H \quad (9)$$

These metrics quantify complementary aspects of signal complexity and scaling behavior [13,14,21].

Multifractal detrended fluctuation analysis (MFDFA) was used to estimate scaling heterogeneity [12]:

$$F_q(s) \sim s^{h(q)} \quad (10)$$

The multifractal spectrum width:

$$\Delta\alpha = \alpha_{\max} - \alpha_{\min} \quad (11)$$

reflects variability of scaling exponents.

Higher $\Delta\alpha$ values indicate increased scaling heterogeneity and may reflect increased complexity, particularly in AFL segments.

Using Takens' embedding theorem [15], the RR series was mapped into phase space:

$$X(t) = [x(t), x(t+\tau), x(t+2\tau)] \quad (12)$$

where τ is the time delay.

This allowed visualization of attractors: compact (sinus rhythm), dispersed (AF), cyclic (AFL) as described in the figure interpretations.

Recurrence plots were constructed according to standard recurrence-analysis principles [22]:

$$R_{i,j} = \Theta\left(\epsilon - \left\|x_i - x_j\right\|\right) \quad (13)$$

where the thresholding term is represented by the Heaviside function.

From these, RQA metrics were derived:

- REC (recurrence rate)
- DET (determinism)
- LAM (laminarity)
- ENTR (entropy)

These quantify structural organization of the signal and reveal degradation during arrhythmias.

Continuous wavelet transform (CWT) was used to examine time-scale structure [23]:

$$W(a,b) = \int x(t)\psi * \left(\frac{t-b}{a}\right) dt \quad (14)$$

where a denotes scale and b denotes translation.

The CWT was used descriptively to compare broadband and more narrowly organized oscillatory activity across the selected rhythm segments.

The full computational workflow included ECG acquisition, filtering and preprocessing, R-peak detection, RR extraction, linear HRV computation, entropy analysis,

fractal and multifractal analysis, attractor reconstruction, recurrence analysis, and visualization. No validated diagnostic classifier was developed.

Implementation tools:

- Python (NumPy, SciPy, NeuroKit2)
- MATLAB (signal processing toolbox)
- SPSS (statistical validation)

2.5. Statistical analysis

Continuous metrics were summarized descriptively by rhythm state. Because the source data comprised heterogeneous public recordings and the analysis was exploratory and methodological, no patient-level causal inference was attempted. Metric differences were interpreted only as descriptive differences among labeled rhythm segments.

Associations among nonlinear indices were evaluated descriptively. No comparison with clinician interpretation, an external reference standard, or a validated diagnostic classifier was performed.

3. Results

The RR-interval analysis identified rhythm-dependent differences in variability, entropy, scaling, and recurrence structure across the selected annotated windows.

The ordered display of baseline, arrhythmic, and post-event windows is descriptively compatible with transitions among dynamical regimes, a concept discussed in nonlinear physiology [2,24].

Within the analyzed windows, AF showed the greatest RR dispersion and entropy, AFL showed a shorter mean RR interval with partially organized high-complexity dynamics, and the post-event segment showed values closer to the sinus-rhythm baseline.

Because the windows were selected retrospectively and do not constitute a prospectively sampled temporal trajectory, these observations do not demonstrate a predictive pre-event phase or establish an early-warning signal. Table 2 summarizes the linear HRV and entropy results.

Table 2. Linear HRV and Entropy Metrics Across Rhythm States

Metric	Sinus	AF (Episode 1)	AFL	AF (Episode 2)	Post-event
Mean RR (ms)	1040	850	520	780	1020
SDNN (ms)	42	138	28	121	45
RMSSD (ms)	30	78	18	64	33
pNN50 after NN filtering (%)	12	3	0	4	13
Shannon Entropy	0.41	0.92	0.61	0.83	0.38
Sample Entropy	0.82	1.65	1.12	1.59	0.79

pNN50 was computed after strict NN-interval filtering and exclusion of ectopic, noisy, or non-analyzable beats. Consequently, low pNN50 values in AF/AFL should not be interpreted as absence of raw RR irregularity. The AFL mean RR of 520 ms corresponds to approximately 115 beats/min in the selected segment; medication and rate-control status were unavailable in the public metadata and are addressed as limitations.

In the selected AF segments, SDNN and entropy were higher than in the sinus-rhythm segment. In AF Episode 2, SDNN was approximately threefold higher than at baseline, consistent with greater RR dispersion and reduced temporal predictability.

The selected AFL segment showed a shorter mean RR interval and lower RMSSD than the AF segments, together with partial structural organization in the nonlinear analyses.

The post-event segment showed several values closer to the sinus-rhythm baseline, although this single window cannot establish physiological recovery or normalization.

These descriptive findings suggest that entropy-based metrics may complement classical HRV measures by quantifying irregularity and reduced predictability; they do not establish diagnostic superiority over standard ECG interpretation.

Table 3. Fractal and Nonlinear Descriptors

Metric	Sinus	AF 1	AFL	AF 2	Post-event
Hurst exponent	0.78	0.63	0.59	0.69	0.81
Higuchi FD	1.24	1.46	1.53	1.41	1.22
Katz FD	1.03	1.27	1.33	1.18	1.02
$\Delta\alpha$ (multifractal width)	0.12	0.41	0.58	0.36	0.10
DET (%)	92	61	39	56	94
ENTR	1.02	1.88	1.71	1.74	0.98

Table 3 shows the following descriptive pattern:

- The Hurst exponent was lower in AF/AFL, consistent with weaker long-range persistence.
- Higuchi and Katz fractal dimensions were higher in the arrhythmic segments.
- Multifractal spectrum width ($\Delta\alpha$) was greater in the arrhythmic segments.
- Determinism (DET) was lower in AF/AFL, indicating less recurrent structure.

Within this small set of windows, AFL had the highest fractal-dimension estimates and multifractal width, indicating a high-complexity but partially organized pattern.

The AF attractors were more diffuse and showed less geometric coherence than the sinus-rhythm and AFL attractors.

Description:

- Sinus rhythm → compact, ellipsoidal attractor
- AF → dispersed, cloud-like attractor
- AFL → cyclic, loop-like attractor

Interpretation

These geometric patterns are compatible with established electrophysiological descriptions [8,10]:

- Sinus rhythm → synchronized conduction
- AF → multiple wandering wavelets
- AFL → stable re-entrant circuit

These plots illustrate that the analyzed arrhythmic signals retained nonrandom geometric structure; they do not prove a specific mechanism or diagnostic class.

In the selected sinus-rhythm segment, recurrence plots showed longer diagonal structures consistent with higher determinism; AF showed more fragmented structures, and AFL showed an intermediate organization.

Recurrence quantification analysis yielded lower DET and higher ENTR values in AF/AFL than in the sinus-rhythm segment, indicating less recurrent organization and greater temporal complexity.

In the selected windows, the sinus-rhythm RR distribution was relatively narrow and unimodal, AF distributions were wider and skewed, and the AFL distribution was narrower but shifted toward shorter intervals. Log-normal and gamma fits were not adequate for all segments; this observation should not be generalized beyond the analyzed windows.

Descriptive co-variation was observed between fractal dimension and entropy, between the Hurst exponent and determinism, and between multifractal spectrum width ($\Delta\alpha$) and overall system complexity.

These patterns suggest a putative cardiac-complexity phase space in which rhythm states may occupy distinct regions, as summarized in Table 4. This interpretation requires confirmation in larger, prospectively defined cohorts.

Table 4. Descriptive summary of rhythm-state complexity patterns.

Rhythm	Observed complexity pattern	Key descriptive features
Sinus	Lower	Higher determinism and a narrower RR distribution
AF	Moderate to high	Greater dispersion, entropy, and reduced geometric coherence
AFL	High	Shorter RR intervals with structured high-complexity dynamics
Post-event	Lower / reconverging	Several metrics closer to the sinus-rhythm baseline

Clinical interpretation of the descriptive findings

Standard electrophysiological descriptions characterize AF as disorganized atrial activation, typical AFL as an organized macro-re-entrant circuit, and ectopy as premature activation arising from focal or multifocal sources [8,10].

In the analyzed segments, fractal metrics differed among rhythm labels. This supports the feasibility of quantitative characterization, but it does not establish superiority over clinician interpretation or a validated diagnostic classifier.

Although FD was higher in selected arrhythmic and nominal pre-event windows, the study was not designed to evaluate prediction. No early-warning claim or predictive threshold can be derived from these data.

Rehabilitation implications remain exploratory. The present data support studying real-time ECG complexity as a research monitoring feature, but no exercise outcomes, adverse events, or patient-reported rehabilitation measures were analyzed.

Overall, the findings indicate that rhythm states can be described using nonlinear descriptors. Fractal dimension and entropy should be regarded as candidate quantitative research features, while clinical and rehabilitation applications remain to be tested.

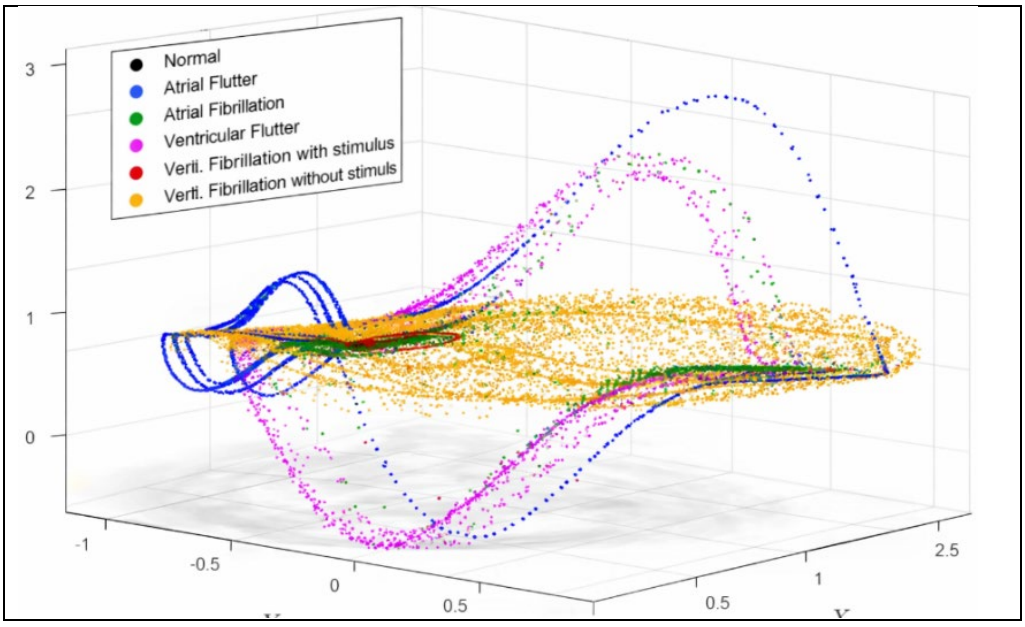

Figure 4. Phase-space attractors corresponding to different cardiac rhythms.

In Figure 4, sinus rhythm displays a compact attractor, while AFL demonstrates cyclic structures. AF exhibits a dispersed, cloud-like geometry, signifying reduced dynamical coherence. These attractor geometries support the interpretation of arrhythmias as distinct dynamical regimes, but the visualizations are not a substitute for formal diagnostic validation.

Additional attractor visualizations are provided for the pre-crisis, AFIB 1, AFL, AFIB 2, and post-crisis periods in Figure 5.

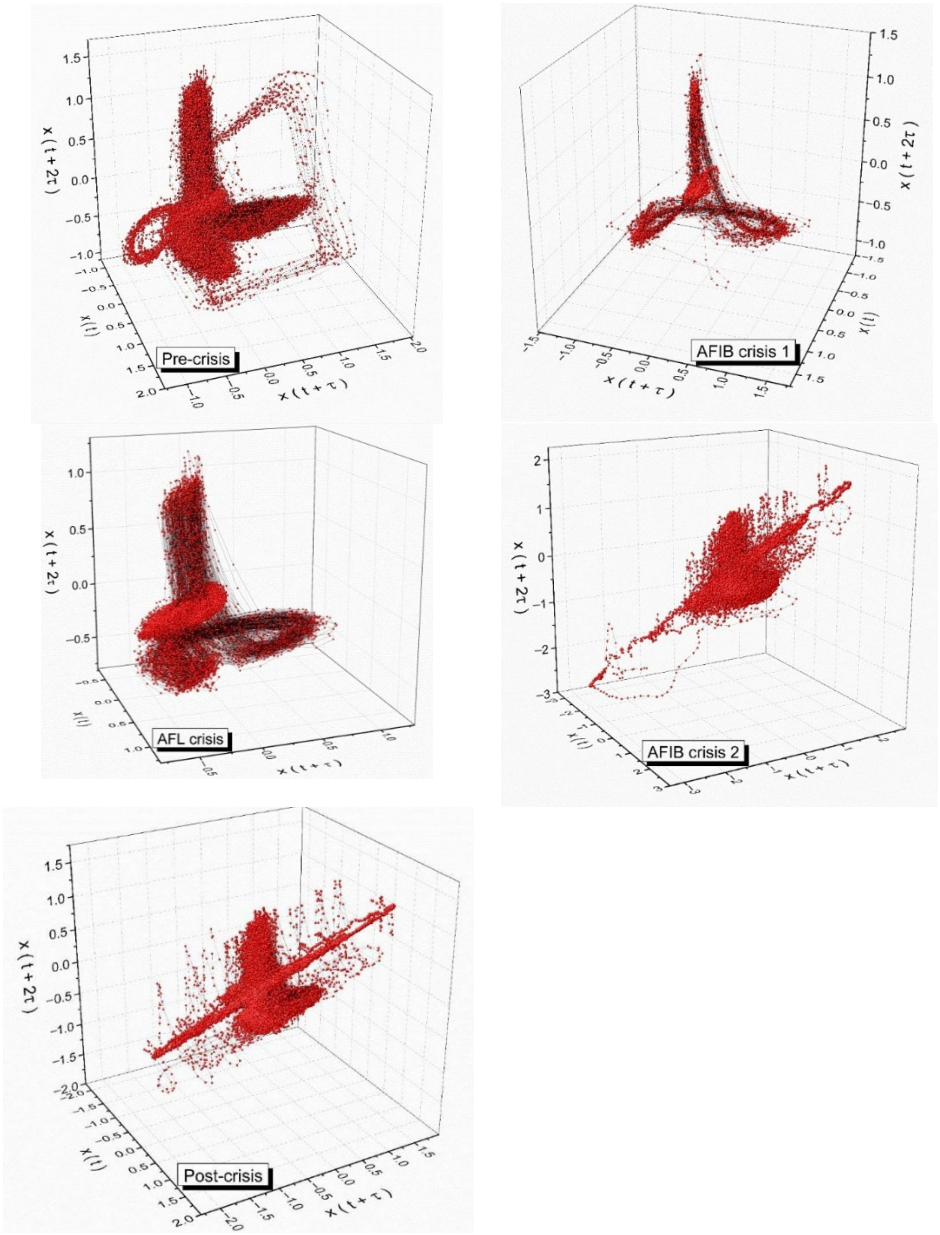

Figure 5. Attractors for the periods: pre-crisis, AFIB 1, AFL, AFIB 2, and post-crisis.

4. Discussion

This study supports examining AF and AFL as dynamical regimes within a nonlinear cardiac system. By combining HRV, entropy, fractal and multifractal measures, recurrence analysis, and attractor-based descriptors, the analysis provides a multimetric profile of rhythm organization rather than relying solely on morphology or average rate.

The selected arrhythmic segments showed greater irregularity, reduced determinism, and altered phase-space structure. AF was characterized by greater dispersion and

reduced geometric coherence, whereas AFL showed a more organized, high-complexity cyclic pattern. These descriptive findings are compatible with established differences between fibrillatory activation and macro-re-entrant flutter circuits [8-10].

Entropy and fractal dimension should be interpreted as complementary descriptors. Entropy reflects unpredictability in beat-to-beat dynamics, whereas fractal measures describe scaling and geometric complexity. Their combined use may improve descriptive characterization of rhythm states, but the present study did not test diagnostic superiority over expert ECG interpretation or a validated automated classifier.

4.1. Implications for Cardiac Rehabilitation Monitoring

Cardiac rehabilitation for patients with AF should be embedded within guideline-directed care that addresses symptoms, rhythm or rate management, comorbidities, risk-factor modification, and individualized physical activity. Exercise prescription should be based on clinical evaluation and established functional measures - not on FD or entropy values - while accounting for ventricular-rate response, medication effects, symptom burden, and coexisting disease [8,9,25-29].

Within cardiac rehabilitation programs, functional capacity can be monitored using cardiopulmonary exercise testing (including peak oxygen uptake when available), submaximal field tests such as the 6-minute walk test, achieved workload, perceived exertion, symptoms, and recovery. Evidence from exercise studies and rehabilitation trials suggests potential improvements in cardiorespiratory fitness, symptom burden, quality of life, and selected AF outcomes, but intervention protocols and populations remain heterogeneous [25-29]. The present study did not measure any of these endpoints.

Wearable or patch-based ECG may support rhythm surveillance during supervised or home-based rehabilitation, but recorded signals must be validated and embedded in a defined workflow for clinician confirmation, alert handling, privacy protection, and escalation of care [30]. In future studies, complexity metrics could be computed as research features alongside standard rhythm, heart-rate, symptom, and workload monitoring; they should not replace conventional ECG interpretation or safety procedures.

A personalized rehabilitation pathway could integrate baseline rhythm phenotype, functional capacity, symptom and patient-reported outcome measures, medication response, and serial wearable data. Prospective protocols should prespecify exercise-tolerance and safety endpoints and compare complexity-informed monitoring with standard rehabilitation monitoring. Nonlinear metrics have been explored in other rehabilitation-related physiological domains, but transfer to AF requires direct validation [31,32].

4.2. Limitations

First, this was a retrospective, segment-level computational analysis of a small number of selected windows from public databases. The segments do not constitute a representative patient cohort, and differences among windows cannot be interpreted as population estimates or causal effects.

Second, the public recordings provided limited patient-level context. Medication use, rate-control status, comorbidities, ablation history, symptoms, functional capacity, and the physiological circumstances surrounding each recording were unavailable or incomplete.

Third, the analysis was descriptive and lacked prospective or external validation. No clinician-accuracy comparison, diagnostic gold-standard comparison, or validated machine-learning classifier was performed; therefore, diagnostic performance and incremental clinical value are unknown.

Fourth, the study included no cardiac rehabilitation outcomes, exercise-tolerance measures, cardiopulmonary exercise testing, 6-minute walk testing, patient-reported outcomes, adherence data, or adverse-event assessment. Consequently, the analysis cannot support exercise prescription or rehabilitation-guided clinical decisions.

Fifth, nonlinear indices are sensitive to segment duration, preprocessing, filtering, artifact handling, embedding parameters, and threshold selection. Synthetic series and illustrative attractors were used only to check algorithms or visualize concepts and cannot establish clinical generalizability. No FD, entropy, or combined-complexity threshold was validated.

5. Conclusions

5.1. General Conclusions

This retrospective segment-level analysis shows that AF and AFL can be described as distinct dynamical patterns within a nonlinear ECG/RR-interval framework, with differences in HRV, entropy, fractal, multifractal, recurrence, and attractor descriptors.

Within the selected windows, AF showed greater RR dispersion and entropy, whereas AFL showed a shorter mean RR interval and higher fractal complexity with partial organization. These findings support the feasibility of a multimetric complexity profile for research-level rhythm characterization.

Fractal dimension and entropy should be considered candidate research descriptors of rhythm instability, not validated biomarkers or clinical decision thresholds.

These descriptors may help frame arrhythmias as dynamical processes, but their predictive and prognostic value must be tested prospectively and externally.

The present analysis supports further investigation of deterministic and chaotic-like properties in cardiovascular physiology without claiming diagnostic, prognostic, or rehabilitation superiority.

The visual and quantitative results were directionally consistent: sinus rhythm showed a more compact and deterministic structure, AF showed greater dispersion, and AFL showed a partially organized high-complexity pattern.

The study does not establish clinical thresholds, early-warning cut-offs, or rehabilitation rules. It provides a methodological basis for prospective evaluation of ECG complexity as a research feature within functional monitoring.

5.2. Theoretical Contributions

This study contributes a reproducible conceptual workflow linking nonlinear ECG analysis with clinical rhythm interpretation. Its primary contribution is methodological integration rather than clinical validation.

5.3. Limitations

The principal limitations are the retrospective segment-level design, reliance on public databases, incomplete patient-level clinical context, unavailable medication and rate-control information, limited segment duration and sample size, descriptive analysis without external validation, no comparison with clinician interpretation or diagnostic classifiers, and the absence of exercise-tolerance measures, rehabilitation outcomes, adverse-event data, and patient-reported outcomes. No FD or entropy threshold was validated.

5.4. Future Research Directions

a. Longitudinal Modeling

Future work should track FD and entropy over time in prospectively enrolled patients and test whether these metrics predict arrhythmia recurrence, functional decline, or other clinically meaningful outcomes.

b. AI Integration

Machine-learning models could be trained to classify rhythm states or predict transitions only after reproducible record-level datasets, prespecified endpoints, and external validation cohorts are available.

c. Multiscale Integration

Combining ECG complexity with imaging, medication status, autonomic testing, biochemical markers, functional capacity, and rehabilitation outcomes may yield a more comprehensive cardiovascular complexity profile.

d. Clinical Trials in Rehabilitation

Prospective rehabilitation studies are needed to test feasibility, safety, exercise tolerance, patient-reported outcomes, adherence, and adverse events, and to determine whether complexity-informed monitoring adds value beyond heart rate, symptoms, functional testing, and standard ECG interpretation.

A conceptual framework for prospective rehabilitation research is presented in Table 5.

Table 5. Conceptual ECG-complexity framework for prospective cardiac rehabilitation research.

Observed FD pattern	Hypothesized monitoring interpretation	Prospective validation requirement
Lower / stable FD	More stable rhythm organization	Compare with exercise tolerance, symptoms, and safety outcomes
Intermediate / rising FD	Possible change in rhythm organization	Test predefined review alerts alongside standard monitoring
High / increasing FD	Higher-complexity rhythm organization	Determine whether supervised reassessment improves safety or outcomes

Note. These categories are conceptual research hypotheses and must not be used as clinical thresholds, exercise-prescription rules, or automated safety decisions.

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References

1. Acharya UR, Paul JK, Kannathal N, Lim CM, Suri JS. Heart rate variability. In: Acharya UR, Suri JS, Spaan JAE, Krishnan SM, editors. Advances in Cardiac Signal Processing. Berlin: Springer; 2007. p. 121-165.
2. Krogh-Madsen T, Christini DJ. Nonlinear dynamics in cardiology. Annu Rev Biomed Eng. 2012;14:179-203.
3. Nayak SK, Bit A, Dey A, Mohapatra B, Pal K. A review of the nonlinear dynamical system analysis of electrocardiogram signal. J Healthc Eng. 2018;2018:6920420.
4. Henriques T, Ribeiro M, Teixeira A, Castro L, Antunes L, Costa-Santos C. Nonlinear methods most applied to heart-rate time series: a review. Entropy. 2020;22:309.
5. Goldberger AL, Amaral LAN, Hausdorff JM, Ivanov PC, Peng CK, Stanley HE. Fractal dynamics in physiology: alterations with disease and aging. Proc Natl Acad Sci USA. 2002;99(Suppl 1):2466-2472.
6. Kantz H, Schreiber T. Nonlinear Time Series Analysis. 2nd ed. Cambridge: Cambridge University Press; 2004.
7. Pincus SM. Approximate entropy as a measure of system complexity. Proc Natl Acad Sci USA. 1991;88:2297-2301.
8. Van Gelder IC, Rienstra M, Bunting KV, et al. 2024 ESC Guidelines for the management of atrial fibrillation developed in collaboration with the European Association for Cardio-Thoracic Surgery (EACTS). Eur Heart J. 2024;45:3314-3414. doi:10.1093/eurheartj/ehae176.

9. Joglar JA, Chung MK, Armbruster AL, et al. 2023 ACC/AHA/ACCP/HRS Guideline for the diagnosis and management of atrial fibrillation. Circulation. 2024;149:e1-e156. doi:10.1161/CIR.0000000000001193.
10. Camm AJ, Luscher TF, Serruys PW, editors. The ESC Textbook of Cardiovascular Medicine. 2nd ed. Oxford: Oxford Univer-sity Press; 2009.
11. Richman JS, Moorman JR. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circ Physiol. 2000;278:H2039-H2049.
12. Ivanov PC, Amaral LAN, Goldberger AL, et al. Multifractality in human heartbeat dynamics. Nature. 1999;399:461-465.
13. Higuchi T. Approach to an irregular time series on the basis of the fractal theory. Physica D. 1988;31:277-283.
14. Katz MJ. Fractals and the analysis of waveforms. Comput Biol Med. 1988;18:145-156.
15. Takens F. Detecting strange attractors in turbulence. In: Rand D, Young LS, editors. Dynamical Systems and Turbulence, Warwick 1980. Lecture Notes in Mathematics. Vol. 898. Berlin: Springer; 1981. p. 366-381.
16. Goldberger AL, Amaral LAN, Glass L, et al. PhysioBank, PhysioToolkit, and PhysioNet: components of a new research resource for complex physiologic signals. Circulation. 2000;101:e215-e220.
17. Moody GB, Mark RG. The impact of the MIT-BIH Arrhythmia Database. IEEE Eng Med Biol Mag. 2001;20:45-50.
18. Pan J, Tompkins WJ. A real-time QRS detection algorithm. IEEE Trans Biomed Eng. 1985;32:230-236.
19. Goldberger AL. Non-linear dynamics for clinicians: chaos theory, fractals, and complexity at the bedside. Lancet. 1996;347:1312-1314.
20. Tesloianu ND, Nedelciuc I, Ghizdovat V, Agop M, Lupascu-Ursulescu C. A fractal physics explanation for acute thrombotic occlusion in an apparently healthy coronary artery. Anatol J Cardiol. 2017;18:155-157.
21. Peng CK, Havlin S, Stanley HE, Goldberger AL. Quantification of scaling exponents and crossover phenomena in nonsta-tionary heartbeat time series. Chaos. 1995;5:82-87.
22. Marwan N, Romano MC, Thiel M, Kurths J. Recurrence plots for the analysis of complex systems. Phys Rep. 2007;438:237-329.
23. Torrence C, Compo GP. A practical guide to wavelet analysis. Bull Am Meteorol Soc. 1998;79:61-78.
24. Glass L. Synchronization and rhythmic processes in physiology. Nature. 2001;410:277-284.
25. Pathak RK, Elliott A, Middeldorp ME, et al. Impact of cardiorespiratory fitness on arrhythmia recurrence in obese individ-uals with atrial fibrillation: the CARDIO-FIT study. J Am Coll Cardiol. 2015;66:985-996.
26. Elliott AD, Verdicchio CV, Mahajan R, et al. An exercise and physical activity program in patients with atrial fibrillation: the ACTIVE-AF randomized controlled trial. JACC Clin Electrophysiol. 2023;9:455-465. doi:10.1016/j.jacep.2022.12.002.
27. Risom SS, Zwisler AD, Sibilitz KL, et al. Cardiac rehabilitation for patients treated for atrial fibrillation with ablation has long-term effects: 12- and 24-month follow-up results from the randomized CopenHeartRFA trial. Arch Phys Med Rehabil. 2020;101:1877-1886. doi:10.1016/j.apmr.2020.06.026.
28. Oesterle A, Giancaterino S, Van Noord MG, et al. Effects of supervised exercise training on atrial fibrillation: a meta-analysis of randomized controlled trials. J Cardiopulm Rehabil Prev. 2022;42:258-265.
29. Buckley BJR, Long L, Lane DA, et al. Exercise based cardiac rehabilitation for atrial fibrillation: Cochrane systematic re-view, meta-analysis, meta-regression and trial sequential analysis. Br J Sports Med. 2025;59:1242-1253. doi:10.1136/bjsports-2024-109149.
30. Varma N, Cygankiewicz I, Turakhia M, et al. 2021 ISHNE/HRS/EHRA/APHRS collaborative statement on mHealth in ar-rhythmia management: digital medical tools for heart rhythm professionals. Eur Heart J Digit Health. 2021;2:7-48. doi:10.1093/ehjdh/ztab001.
31. Pintilie A, Paduraru O, Costescu E, Ursescu C, Popescu M, Streinu-Cercel A. Restoring respiratory complexity: a fractal approach to post-COVID pulmonary rehabilitation. Balneo PRM Res J. 2026;17(1). doi:10.12680/balneo.2026.959.
32. Ursescu C, Costescu E, Popescu MN, Tabrean MC, Berteanu M. Modeling post-COVID respiratory rehabilitation with non-linear dynamics and fractal metrics: beyond spirometry. Balneo PRM Res J. 2025;16(4). doi:10.12680/balneo.2025.901