ECG and Nonlinear HRV Analysis: Assessing Stress Recovery Before and After Academic Exams

TEAM BYZNESS
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Abstract

This study examines how academic stress affects the Autonomic Nervous System (ANS) in 12 postgraduate students. We used a custom Python pipeline to analyze single-lead ECG signals recorded in two situations: just before an exam (anticipatory stress) and just after (recovery/rumination). We compared the sensitivity of standard linear HRV metrics with advanced nonlinear complexity measures.

Our analysis revealed a "Heart Rate Paradox": not all students recovered after exams. A specific "Ruminator" type—students with persistent stress and recurring thoughts—showed sustained arousal even after the stressor was gone. Nonlinear metrics, especially the Higuchi Fractal Dimension ($p = 0.06$), showed a consistent loss of physiological complexity post-exam, regardless of heart rate trends. These results suggest cognitive stress shifts the body from complex balance to rigidity.

1. Introduction

The physiological response to stress is controlled by the Autonomic Nervous System (ANS), which is a key component of biomedical signal processing. The ANS has two branches: the Sympathetic Nervous System (SNS), which manages the "fight or flight" response, and the Parasympathetic Nervous System (PNS), which handles "rest and digest" functions. In healthy people, heart rate constantly changes in complex patterns due to the interplay of these systems. This is called Heart Rate Variability (HRV). Understanding these dynamics matters, especially under cognitive and emotional stress.

Building on this understanding, academic examinations create a specific type of stress that demands high mental effort. While mean Heart Rate (HR) is widely used to detect stress, it does not always capture the complexities of the autonomic system's response. A person might look calm and have a steady heart rate, but reduced parasympathetic activity, known as vagal withdrawal, can still occur. Ending the stressful event does not automatically mean the body has recovered. Continued thoughts about the exam, called 'rumination,' can keep the body's stress system active long after the exam, as the mind continues to process how it went.

The primary objective of this project is to advance beyond traditional linear heart rate (HR) analysis. The specific aims are as follows:

1. Develop a comprehensive end-to-end signal processing pipeline for raw electrocardiogram (ECG) data, encompassing data loading, filtering, and peak detection.
2. Compare the sensitivity of time-domain and frequency-domain metrics to non-linear complexity measures, such as fractal dimension and entropy.
3. Analyze demographic variables, such as age and region, to identify resilience factors within an

international student cohort.

2. Dataset and Experimental Protocol

2.1 Subjects

The dataset consists of recordings from 12 postgraduate students (aged 22-26) enrolled in the Erasmus Mundus IPCV program. The cohort demonstrates demographic diversity, with participants from Europe, South Asia, the Middle East, and South America. This diversity facilitates preliminary analysis of cultural and regional variations in stress responses.

2.2 Data Acquisition

After identifying the subject cohort, data were collected using a single-lead ECG sensor with a sampling frequency of 250 Hz. To assess acute anxiety effects, two 30-second recordings were obtained from each participant.

- Condition A (Before Exam) was recorded immediately prior to a major examination, representing anticipatory stress.
- Condition B (After Exam) was recorded immediately after the examination and represents the recovery or rumination phase.

2.3 Data Format

The signals were stored in raw binary (.dat) format with int16 digitization. Because the hardware lacked pre-filtering, a comprehensive software filtering pipeline was required to maintain signal integrity for stress analysis.

3. Methodology

A custom signal processing pipeline was built in Python. It converts raw ECG data into usable physiological metrics. The modular pipeline has sequential steps for data loading, noise removal, peak finding, and feature extraction.

3.1 Signal Pre-processing and Artifact Removal

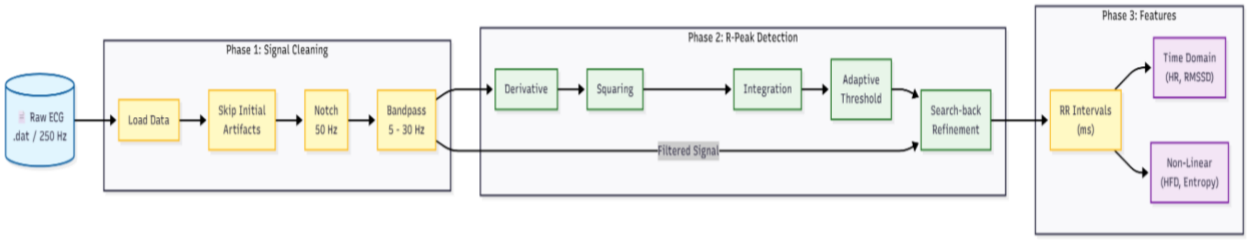
The raw electrocardiogram data were stored in binary .dat format with int16 digitization. Because standard headers were missing, a heuristic loading procedure was used, discarding the initial 50 samples to avoid header artifacts and baseline distortion. Once loading was complete, the signal underwent a two-stage filtering process to maximize the Signal-to-Noise Ratio (SNR) of the QRS complex.

To address the specific noise characteristics of the recording environment, an Infinite Impulse Response (IIR) Notch filter centered at 50 Hz (Quality Factor $Q = 30$) was applied. This approach removed powerline interference characteristic of the European electrical grid without degrading adjacent frequency components. Subsequently, a 3rd-order Butterworth bandpass filter with a passband of 5–30 Hz was used. This frequency range was chosen to isolate the primary energy of the QRS complex and to attenuate low-frequency baseline wander from respiration (< 0.5 Hz) and high-frequency electromyographic noise. Zero-phase filtering (forward-backward application) was employed to ensure the temporal positions of the R-peaks remained undistorted relative to the raw signal.

Implementation Note:

The bandpass filter is implemented as a 3rd-order Butterworth IIR filter in SciPy. The passband 5–30 Hz was chosen to preserve QRS energy while excluding high-frequency EMG noise. A 50 Hz notch filter with $Q = 30$ is applied beforehand to remove mains interference.

Figure 1: End-to-End Flowchart of the Custom Biomedical Signal Processing Pipeline



3.2 R-Peak Detection Algorithm

Accurate R-peak detection is essential for Heart Rate Variability (HRV) analysis. This study implemented a modified Pan-Tompkins algorithm, specifically optimized for short-duration signals. The detection process comprises four sequential transformations:

1. Gradient Extraction: The filtered signal, pre-processed to remove baseline wander and high-frequency noise, is differentiated to emphasize the steep slopes characteristic of the R-wave. This step suppresses lower-frequency P and T waves.
2. Non-Linear Amplification: The derivative signal is squared (y_n^2). This non-linear operation amplifies the high-amplitude differences of the QRS complex and further suppresses smaller noise spikes.
3. Envelope Generation: Moving window integration is applied to the squared signal. A window width of 150 ms merges the QRS features into a smooth waveform envelope.

Implementation Details:

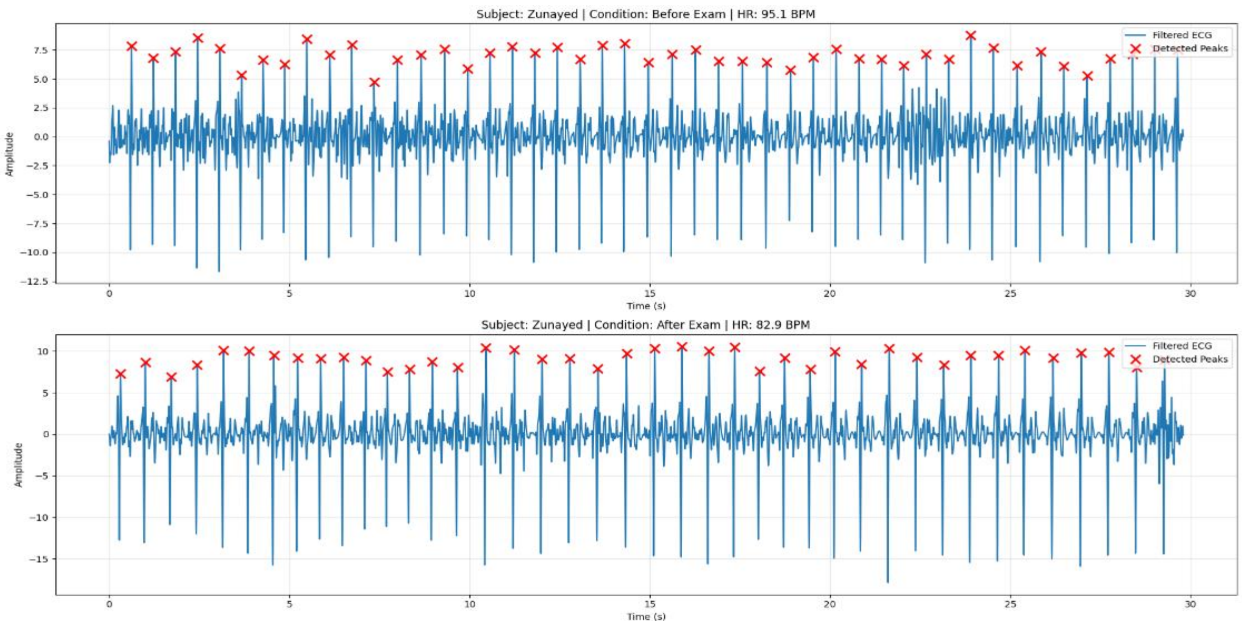
1. The moving-window integration uses a window length of 150ms**.**
2. The initial detection threshold is set as 2 × mean(envelope).
3. Because moving-window integration shifts peaks, a ±100ms search-back window is applied to recover the true R-peak from the filtered ECG.

Adaptive Thresholding and Refinement: Peaks are initially identified in the envelope using a dynamic threshold set at twice the mean signal amplitude. A search-back refinement step is subsequently applied. Since the integration window shifts the peak location, the algorithm examines the original filtered signal within a ±100ms window of the detected envelope peak. This procedure ensures ms-level precision in the final RR-interval calculation.

Figure 2: Comparison of Raw and Filtered ECG Signal with Detected R-peaks

3.3 Feature Engineering

Over 30 metrics were computed from the extracted RR-intervals (the time differences between consecutive heartbeats) across three physiological domains to capture distinct aspects of autonomic control.



Time-domain analysis focused on the variance between beat-to-beat intervals. The Root Mean Square of Successive Differences (RMSSD), a primary marker for vagal tone (parasympathetic activity, which refers to nervous system responses that promote rest and relaxation), and pNN50, the percentage of successive intervals differing by more than 50 ms (which is another indicator of parasympathetic activity), were calculated.

Frequency-domain analysis was performed using Welch's periodogram. The unevenly sampled RR series was interpolated at 4 Hz using linear interpolation (np.interp) to create a uniformly sampled tachogram suitable for Welch's method. The interpolation frequency was set to 4 Hz, matching standard short-term HRV preprocessing guidelines. Power spectral density was integrated in the low-frequency (0.04–0.15 Hz) and high-frequency (0.15–0.40 Hz) bands. The resulting LF/HF ratio was calculated as a proxy for sympathovagal balance, with higher ratios typically indicating sympathetic dominance (stress).

Nonlinear complexity analysis was employed to test the hypothesis that stress reduces physiological complexity (i.e., the degree of variability and unpredictability in physiological signals). Two advanced metrics were utilized:

1. Higuchi Fractal Dimension (HFD): Calculated with a maximum interval parameter
   k max=5. A low k max was selected because RR sequences from 30-second windows contain limited samples (30 beats), and larger kmax values become unstable for short recordings. This metric quantifies the roughness or self-similarity (i.e., the occurrence of repeating patterns at different scales) of the heart rate time series.
2. Sample Entropy (SampEn): Calculated with an embedding dimension $m = 2$ and tolerance $r = 0.2 * SD$. This metric measures the signal's unpredictability. Lower entropy indicates a more repetitive and rigid system.

4. Experiments and Analysis

Our experimental analysis indicated that students respond differently to academic stress, displaying a biphasic pattern. When comparing the anticipatory ("Before") and recovery ("After") conditions, we observed clear differences in stress regulation of the autonomic systems.

4.1 The Heart Rate Paradox: Recoverers vs. Ruminators

It was hypothesized that completing the exam would decrease heart rate among all students. However, the cohort was divided into two phenotypes (see Figure 3). Approximately 58% of students, designated as "The Recoverers," exhibited the anticipated physiological relief: heart rate decreased by more than 10 BPM, and vagal tone (RMSSD) rebounded immediately following the exam. These findings indicate effective re-engagement of the parasympathetic nervous system. This classification was conceptual and based on visual inspection. The Python pipeline does not currently implement an automated threshold or clustering algorithm for assigning “Recoverer” or “Ruminator” labels. In contrast, the remaining 42%, identified as "The Ruminators," exhibited a paradoxical response. These students demonstrated either stagnation or an increase in heart rate, accompanied by a continued decline in vagal tone after the exam concluded. This observation suggests that, for a substantial subset of students, the cessation of the external stressor does not initiate physiological recovery. Persistent rumination, defined as the cognitive process of replaying exam questions or worrying about grades, likely sustains sympathetic arousal and prolongs the physiological stress response.

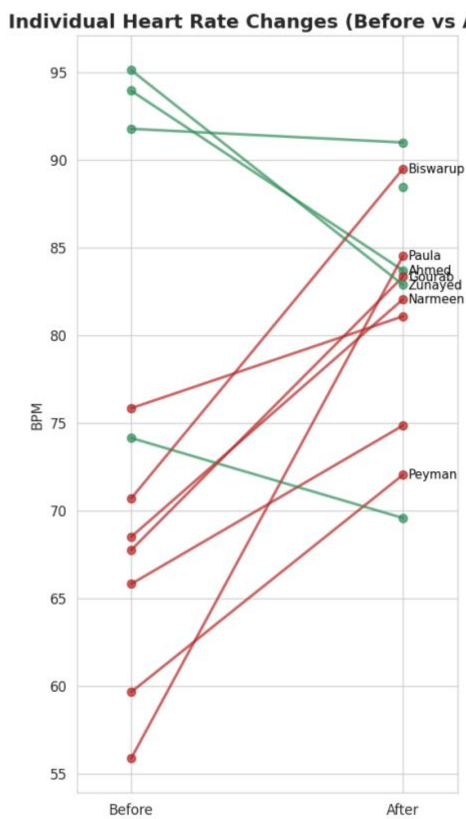


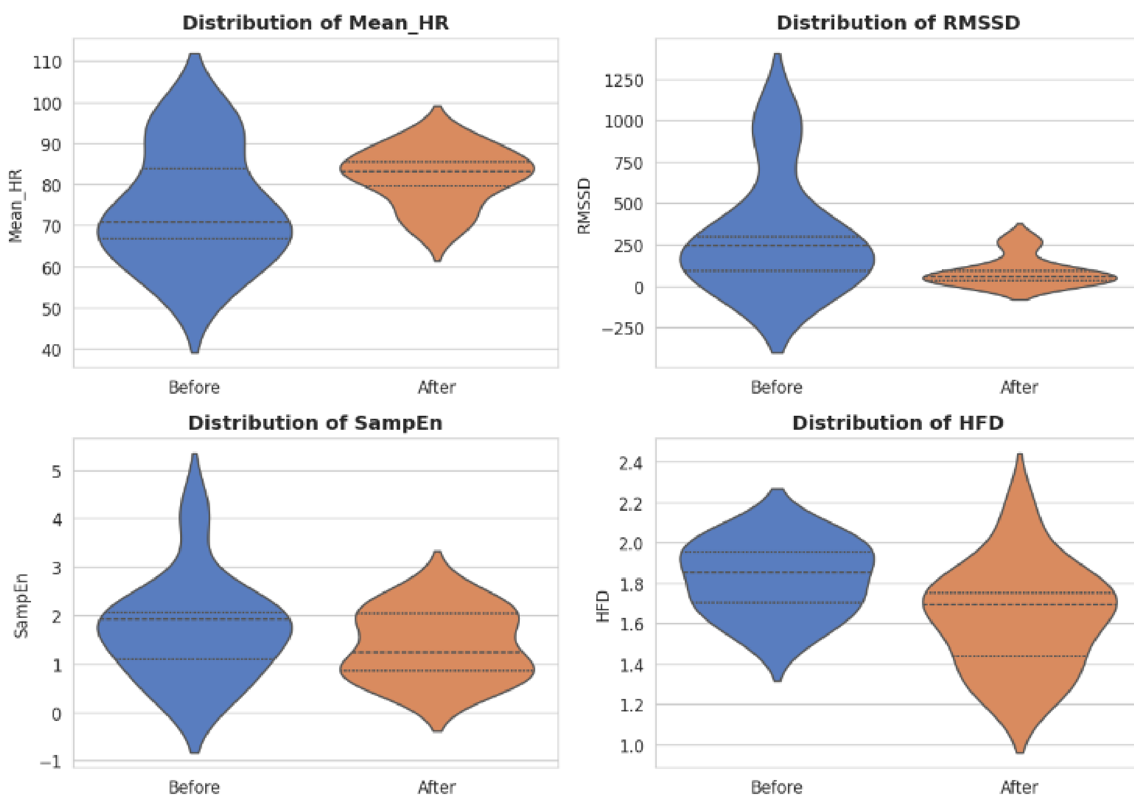
Figure 3: Paired Heart Rate (HR) Changes Comparing "Recoverer" and "Ruminator" Phenotypes

4.2 Complexity as a Universal Marker

Although linear heart rate metrics showed inconsistent results across the population ($p = 0.10$), nonlinear complexity metrics provided a more consistent assessment of the stress state. Statistical analysis of the Higuchi Fractal Dimension (HFD) revealed a near-universal decrease in the 'After' condition ($p = 0.06$).

Together, these findings support the "Loss of Complexity" hypothesis proposed by Goldberger et al. Students who recovered in terms of pulse rate frequently exhibited a lower Fractal Dimension, indicating that the exam induced a transition from complex homeodynamics to a mechanically rigid rhythm. This evidence implies that, whereas heart rate responds to immediate metabolic demand, Fractal Dimension reflects the persistent rigidity of the autonomic nervous system under cognitive load.

Figure 4: Violin Plots Comparing Higuchi Fractal Dimension (HFD) Distributions for Anticipatory Stress and Recovery Conditions



4.3 Demographic Correlations

Demographic analysis yielded additional insights into resilience factors. A strong positive correlation ($r = 0.54$) was observed between age and Vagal Tone (RMSSD) retention. Older master's students exhibited greater coping capacity with the stressor, displaying less autonomic withdrawal compared to younger participants. This difference may be attributable to accumulated experience or more effective emotional regulation.

Gender analysis indicated that female participants in this cohort exhibited greater physiological reactivity, as evidenced by larger percentage fluctuations in heart rate compared to males. Regarding regional differences, students from the Middle East demonstrated the highest resilience metrics, whereas the European cluster exhibited the most pronounced anticipatory anxiety. However, due to the limited sample size ($N = 12$), these demographic trends should be interpreted as descriptive rather than statistically generalizable.

Please Note, all p-values reported in this section come from two-tailed paired-sample Pearson correlation tests. For before–after comparisons, deltas (After − Before) were used.

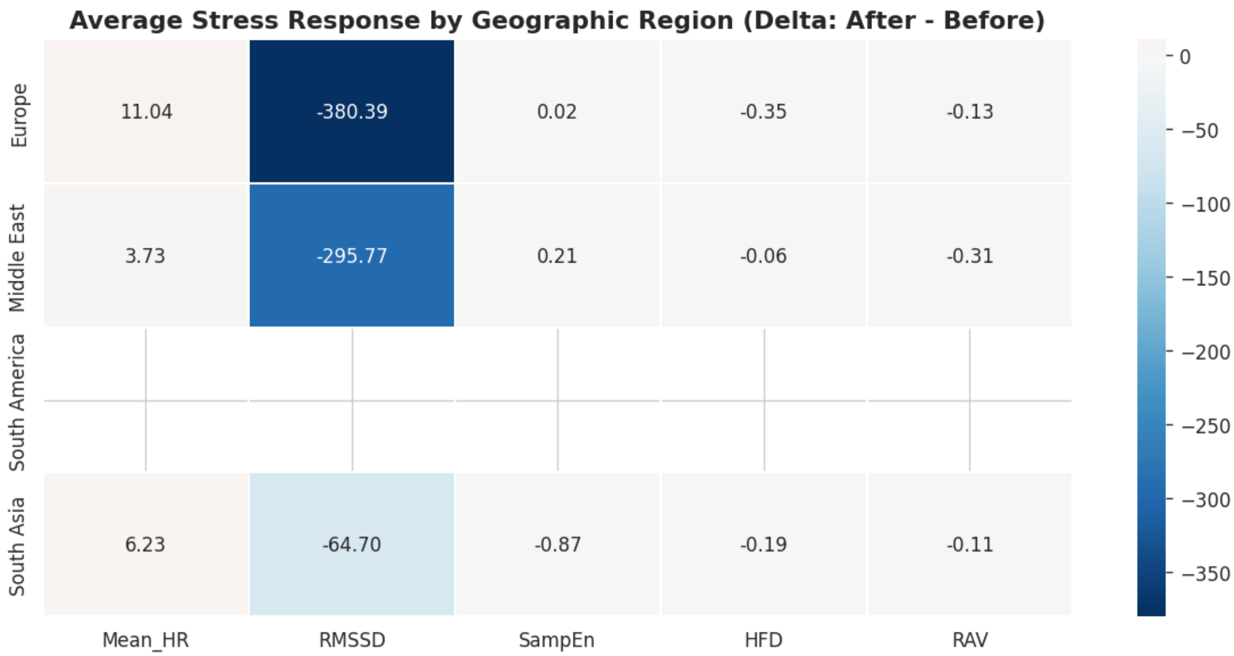


Figure 5: Average Autonomic Stress Response by Geographic Region (Delta: After – Before)

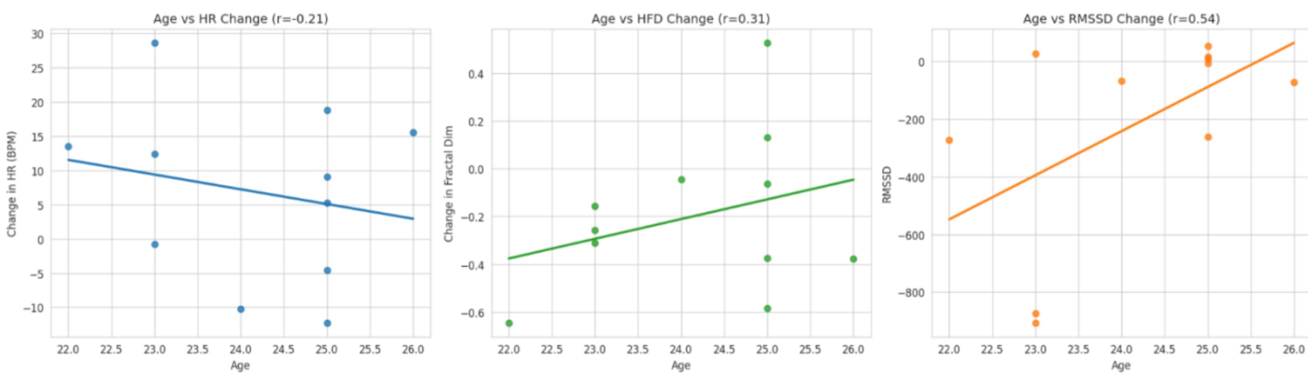


Figure 6: Correlation Between Age and Physiological Stress Response (Delta: After – Before)

5. Conclusion

This study established a biomedical signal processing pipeline to examine physiological responses to academic stress. Raw electrocardiogram (ECG) data were filtered and peak-detected, enabling comparison between standard heart rate metrics and nonlinear complexity measures.

The analysis produced two main physiological insights. First, in terms of autonomic response, the study identified the "Ruminator" phenotype. This group, which made up about 40% of participants, showed that the end of an exam does not always lead to rapid autonomic recovery. For them, sympathetic arousal continued after the stressor was removed. Second, when considering stress markers, the Higuchi Fractal Dimension (HFD) was more reliable than mean heart rate. Heart rate trends varied among participants, but almost all showed a decrease in fractal complexity after the exam. This suggests that cognitive load reduces cardiac rhythm flexibility. Nonetheless, interpreting these results is constrained by the study design. The main limitation was the 30-second recording period. Although this duration is sufficient for time-domain and fractal evaluation, it does not meet the conventional clinical recommendation for frequency-domain (LF/HF) analysis, thereby reducing the reliability of spectral outcomes. Additionally, the small sample (N=12) limits the statistical reliability of demographic associations.

In summary, these findings show that nonlinear dynamics can identify stress states that linear metrics miss, especially in short recordings. For future validation, the data collection window should be extended to five minutes to meet standard HRV guidelines, and more participants should be recruited to separate real trends from individual variability.

References

1. Pan, J., & Tompkins, W. J. (1985). A real-time QRS detection algorithm. *IEEE Trans. Biomed. Eng.*
2. Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. *Frontiers in Public Health.*
3. Goldberger, A. L., et al. (2002). Fractal dynamics in physiology: alterations with disease and aging. *PNAS.*
4. *Brosschot, J. F., et al. (2006). Perseverative cognition, cardiovascular reactivity, and somatic health. Journal of Psychosomatic Research.*
5. *Task Force of the European Society of Cardiology. (1996). Heart rate variability: standards of measurement, physiological interpretation and clinical use.*