Computers in Biology and Medicine 213 (2026) 111853

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

A broken power-law model of heart rate variability spectra in sleep

Bence Schneider[a,*], Martin Dresler[b], Ferenc Gombos[c,d], Ilona Kovács[c,e], Róbert Bódizs[a]

[a] Institute of Behavioural Sciences, Semmelweis University, Budapest, Hungary
[b] Radboud University Medical Center, Donders Institute for Brain, Cognition and Behavior, Nijmegen, Netherlands
[c] HUN-REN-ELTE-PPKE Adolescent Development Research Group, Budapest, Hungary
[d] Laboratory for Psychological Research, Pázmány Péter Catholic University, Budapest, Hungary
[e] Faculty of Education and Psychology, Eötvös Loránd University, Budapest, Hungary

HIGHLIGHTS

- The power-spectrum of heart rate variability in sleep follows a broken power-law, characterizable by two-slopes, separated by a breakpoint, indicating fractal properties of the interbeat interval series.
- Aging is associated with a shift of the spectrum toward lower frequencies–marked by decreases in the high-frequency intercept, breakpoint frequency, and low-frequency peak frequency.
- Most variance in LF/HF band power is explained by changes in the fractal parameters, not oscillatory activity.

ARTICLE INFO

Keywords:
Heart rate variability
Electrocardiography
Spectral analysis
Fractal
Power-law

ABSTRACT

A parametric description of RR-interval spectra was introduced in the study, using a broken power-law model in addition to the parametrization of oscillatory peaks. Then, the model was used to evaluate effects of age, sex and sleep architecture on heart rate variability (HRV) in healthy subjects. From a polysomnography database, 215 whole-night electrocardiograms (ECGs) were extracted. The fractal and oscillatory power-spectral densities (PSDs) were calculated from RR-intervals, then a broken power-law model was fitted using piecewise linear regression to the double-logarithmic PSD, determining a breaking point in the fractal component, and allowing for two independent spectral slopes in the lower and higher frequency domains. The two-slope model provided a more optimal description compared to linear regression, even when penalizing increased model complexity. Peak detection was applied to the oscillatory component in the LF (0.04–0.15 Hz) and HF (0.15–0.4 Hz) bands, extracting the frequency and prominence of the dominant peak from each. The high frequency domain intercept, the breaking point frequency and the LF peak frequency decreased significantly with age. Both slopes were flatter in females, while the high domain intercept and the HF peak prominence were significantly increased. Waking after sleep onset and lightest sleep (N1) were associated with lower intercept values, while REM sleep had an opposite effect. The broken power-law model proved to be appropriate for the description of RR-interval spectra, and captured effects of age, sex and sleep structure that were corroborated by the literature. We would like to highlight that while HRV changes are often assumed to be of oscillatory origin, the fractal component has a major contribution to the total PSD, and thus to all measures derived from it.

1. Introduction

Biological rhythms in the human body are generally complex as they are a result of multi-level interactions spanning several spatial and temporal scales. The modulation of the heart rate is no exception, being influenced by molecular factors on the millisecond scale, autonomic nervous regulation from seconds to minutes, endocrine effects at the minute to hour rate, and variations in gene transcription on the order of hours/days. Besides endogenous effects, the healthy heart rate constantly adapts to externally determined physical conditions and psychological cues [19]. The degree of this variability can be quantified by heart rate variability (HRV) indices, which express the beat-to-beat time interval variance over a given period, and can be measured by

* Corresponding author.
Email address: schbenc@gmail.com (B. Schneider).

https://doi.org/10.1016/j.compbiomed.2026.111853
Received 2 April 2026; Received in revised form 2 July 2026; Accepted 4 July 2026
Available online 9 July 2026

RR-interval changes in the electrocardiogram (ECG). In addition to cardiovascular diseases and autonomic neuropathies, altered HRV values are observed in numerous psychopathologies, such as depression, anxiety disorders, bipolar disorder, ADHD, schizophrenia, and mild cognitive impairment [5]. Sleep is a state during which most external stimuli are ignored, as a consequence it provides a window on endogenous modulations of different physiological systems, a prominent example being the processes in the autonomic nervous system (ANS). Besides cardiovascular regulation, both the sympathetic and vagal branches of the ANS play an important role in sleep initiation and homeostasis, forming a bidirectional link between heart and sleep dynamics, HRV is an indicator of cardiac and sleep health alike. Heart rate variability is atypical in primary sleep disorders like insomnia, or sleep disordered breathing diseases, the most common being obstructive sleep apnea [31]. At the same time, improper sleep is known to contribute to a range of cardiovascular diseases [20]. Apart from pathologies, significant changes in the ANS also occur with aging, affecting many systems, and manifesting as alterations in blood pressure, heart rate, breathing, digestion and sleep. With the dysregulation of the ANS, the adaptivity of the system is reduced, which is also reflected by decreased HRV values [1].

Beyond the fluctuation of interbeat intervals expressed by the time-domain HRV indices, it is possible to gain information about the contribution of different frequencies to this total variance by computing the power-spectral density (PSD) of RR-interval series. Examining the RR-interval power spectra, characteristic oscillatory peaks have been identified and the so-called low frequency 0.04–0.15 Hz (LF) and high frequency 0.15–0.4 Hz (HF) bands were established in the frequency domain HRV methodology, as these bands usually contain the oscillations corresponding to Mayer waves (0.1 Hz) and to respiratory sinus arrhythmia (0.2 Hz). Their increased power has been conventionally attributed to sympathetic and parasympathetic cardiac nerve activation respectively. Subsequently, the LF/HF power ratio has been proposed as a compact indicator of sympatho-vagal balance. However, it has been noted that the correspondence of sympathetic and vagal activation to the LF and HF band powers might not be so straightforward, but rather a more complex interaction, and that the proportionalization of the two band-powers further contracts the sympathetic, parasympathetic and possibly other underlying independent factors into a single measure [3].

As with many other electrophysiological signals (local field potentials, electrocorticograms, electroencephalograms, magnetoencephalograms), the RR-interval time series also contains an aperiodic component besides oscillations. The approach of separating the oscillatory and aperiodic components of the spectrum has gained popularity in the field of electroencephalography [7,33] as changes in the aperiodic component carry meaningful information about brain states [6,18,28]. Thus, untangling the oscillatory and aperiodic contributions could be important in the case of HRV signals as well, as they might reflect different underlying heartbeat regulation mechanisms, which traditional band-based approaches (like calculating the total, LF or HF powers) might conflate. It has been revealed that heart rate fluctuations not only conform to a power-law PSD characterized by physiologically and cardiologically relevant parameters [2,16], but also uncover a fractal temporal structure of the underlying tachogram [34]. Moreover, the known multifractal nature of RR-interval time series appears to be an essential property of healthy heart functioning [12,22], and possibly a consequence of modulatory mechanisms spanning several temporal scales [19], which further indicates that a multi-exponent description of the RR-interval spectra is necessary.

Power-law behaviour with a breaking point was evidenced in the non-harmonic component of the 24-hour spectral analysis of the heart rate [26]. In a similar approach, our aim is to uncover the fundamental aspects of the sleep-related multi-exponent human RR-interval spectra. Our study presents effects of aging and sex on heart rate variability during sleep in a healthy population, using a parametric description of RR-interval power spectra, through the adoption of a broken power-law model characterizing the fractal component with two spectral slopes and intercepts separated by a custom breaking-point, in addition to the parametrization of the LF and HF band peaks. Furthermore, we investigate the relationship between fractal and oscillatory spectral parameters to classical HRV measures and sleep macrostructure indicators. Based on the evidence supporting the multifractality of the time series representing healthy human RR sequences [12,22], as well as the relationship between the fractal scalings in the time and the frequency domain, we hypothesize that heartbeat dynamics during sleep follow a broken power law-type spectra, with two exponents and a breaking point. Moreover, we hypothesize that oscillations corresponding to Mayer waves (≈0.1 Hz) and to respiratory sinus arrhythmia (≈0.2 Hz) are forming non-fractal, periodic activities, which lead to spectral peaks at respective frequencies. Furthermore, we hypothesize that known age- and sex differences in heart rate dynamics are reflected in the parameters describing multifractal and oscillatory activities of the human RR-spectra during sleep. Last, but not least, we hypothesize that objective, polysomnography-based differences in sleep quality are reflected in fractal and oscillatory measures of RR time series spectra.

2. Methods

Full-night ECG recordings were extracted from an already existing polysomnography database of 251 healthy humans from a wide age range (4–69 years), including 122 females (Budapest-Munich database). Subjects had given their written consent for inclusion in the database and the multilaboratory data collection procedures had been approved by corresponding local ethical committees, all respecting the Declaration of Helsinki [4]. The polysomnographic recordings included EEG derivations in the 10–20 system, and were scored manually according to the AASM standards [11] with the exception of a custom epoch length of 20 s for staging (adopted from the Rechtschaffen and Kales system [24], which yields a slightly better resolution of sleep stages than the standard 30s epochs), and 4 s for artifact annotation. The duration of records varied between 212 and 729min (mean: 513.44min, SD:63.06min). All records contained one bipolar ECG derivation according to the polysomnography standards. R-peaks were automatically detected, and the evenly resampled (4 Hz sampling rate) RR-interval time series were constructed using the Kubios HRV software [30]. Missing segments due to artifact removal in the series were replaced with values linearly interpolated between the last and first values before and after the gaps. Recordings that contained more than 10% missing values were excluded from the analysis, leaving 215 high-quality RR-interval series (103 females, age range: 4–69, mean: 26.44 years). The fractal and oscillatory PSD of the whole-night RR-interval time series were calculated using the Irregular-Resampling Auto-Spectral Analysis (IRASA) method [33], in the frequency range of 0.001–0.5 Hz, using a moving window of 4096 s.

2.1. Parametrization of the fractal component

Transforming both the power and frequency axes of the fractal component of the PSD into logarithmic space, it can be noted that the relationship between power and frequency is described by a broken power-law [see Fig. 1. left]. After uniform resampling of the PSD in the logarithmic frequency domain, piecewise linear regression [13] was applied to the fractal component, which automatically locates a breaking point and determines slope and intercept values of two linear functions for the lower and higher frequency domains. To confirm that the broken power-law model was more appropriate than the single slope description, the Akaike information criterion was calculated for simple linear and two-slope piecewise regressions in the log-log domain. Lower Akaike information criterion values indicate better model fits. As the metric is derived from the residual sum of squares but includes a penalty term for the number of model parameters, overfitting and unnecessary model complexity can thus be avoided, in contrast to simple goodness-of-fit metrics like the R2 coefficient of determination [10].

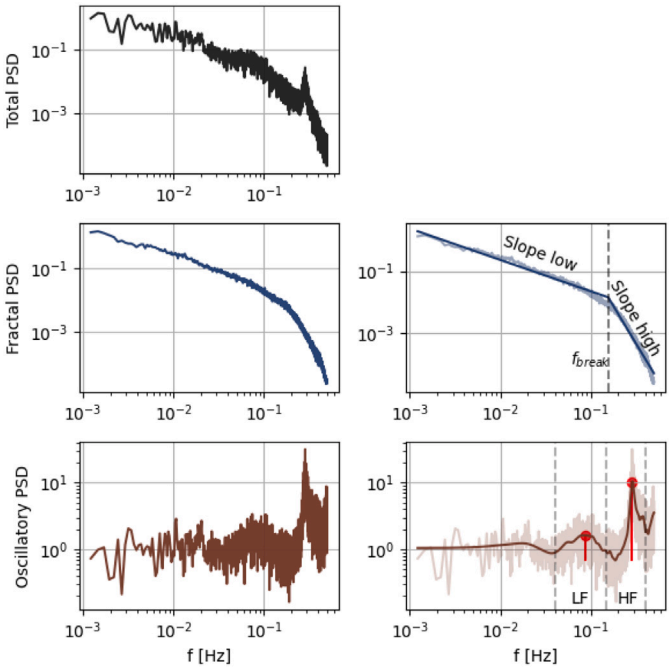

Fig. 1. Total RR-interval power-density spectra (top left), fractal component separated by IRASA (middle left) and the fitted piecewise linear function (middle right). The oscillatory component (bottom left) and peaks detected in the LF and HF bands after Gaussian smoothing (bottom right).

2.2. Parametrization of the oscillatory component

The oscillatory PSD was established by subtracting the fractal component from the total PSD in the log-log space, then smoothed with a Gaussian filter (the standard deviation of the Gaussian kernel was 20 samples). The frequencies and prominences of the dominant peaks were extracted via a peak detection algorithm [32] in the low frequency (LF) 0.04–0.15 Hz and high frequency (HF) 0.15–0.4 Hz bands commonly used in HRV analyses.

2.3. Statistics and sleep indicators

After extracting the spectral parameters, ANCOVA analysis was carried out for each parameter as the dependent variable with sex as a fixed factor and age as a covariate. Using manually scored and validated hypnograms from the polysomnography database, macrostructure indicators were calculated. The indicators included total sleep time (TST, duration of all sleep stages in the recording), sleep efficiency (SE, ratio of TST compared to the duration of the recording), wake after sleep onset (WASO, total time in wake state after the first N2 and last sleep stage) and the percentage of each sleep stage (compared to the time between the first N2 sleep and last sleep stage). These were then Pearson-correlated with the overnight spectral parameters of heart rate. Correlations were considered significant after Holm–Bonferroni correction ($p_k < \frac{0.005}{(m-k+1)}; 1 < k < m; m = 63;$).

Classical HRV indicators were also calculated, the HRV index (total spectral power), then LF and HF power, and finally the LF/HF ratio. Multiple linear regression was carried out for each classical HRV marker as the dependent variable with groups of spectral parameters as predictors.

3. Results

3.1. Multifractality of human heart rate dynamics during sleep

We revealed a lower Akaike Information Criterion value for the two-slope models in all 215 cases, suggesting a better model fit with two spectral slopes as compared to the classical single exponent solutions reported in the literature on the power law scaling of the Fourier transform-derived periodogram of human RR series. The overall descriptives of the spectral parameters show that the spectral slope was generally flatter in the low frequency domain (M = −0.723) than in the high domain (M = −3.916), the difference between the two slopes being positive in all cases. Besides that the breaking point frequency varies in a wide range (range = 0.010-0.358 Hz). The coefficients of determination (R-squared) for the piecewise regression indicated adequate fits for the fractal PSD component (mean = 0.983, range = 0.944-0.997), for more details see Table 1 (Table 2).

Table 1
Descriptives of the fractal spectral parameters.

	Slope low	Slope high	Slope diff.	Inter. low	Inter. high	f_{break}	R^2
Valid	215	215	215	215	215	215	215
Missing	0	0	0	0	0	0	0
Mean	−0.723	−3.916	3.193	−5.889	−11.783	0.147	0.983
SD.	0.182	1.748	1.673	0.862	1.769	0.080	0.008
Min.	−1.314	−8.605	0.501	−9.869	−18.051	0.010	0.944
Max	−0.233	−1.179	7.769	−3.402	−7.870	0.358	0.997

Table 2
Descriptive statistics of the oscillatory spectral parameters.(f - peak frequency, p - peak prominence, LF - low frequency band, HF - high frequency band.)

	f_{LF}	f_{HF}	p_{LF}	p_{HF}
Valid	209	213	209	213
Missing	6	2	6	2
Mean	0.081	0.257	0.541	2.039
SD.	0.015	0.041	0.218	0.582
Min.	0.043	0.178	0.213	0.354
Max	0.129	0.381	1.432	3.509

3.2. Age effects

A high frequency domain intercept decrease was observed with aging [$F(1212) = 19.107$, $p < 0.001$, $\eta_p^2 = 0.083$], while the breaking point frequency also showed a decreasing tendency [$F(1206) = 18.08$, $p < 0.001$, $\eta_p^2 = 0.022$]. Oscillatory peak frequency exhibited slowing as age advances in the LF domain [$F(1206) = 11.502$, $p < 0.001$, $\eta_p^2 = 0.053$].

3.3. Sex effects

Significant effects of sex were found both in the low domain slope [$M_{female} = -0.680$, $SD_{female} = 0.165$, $M_{male} = -0.764$, $SD_{male} = 0.189$, $F(1,212) = 11.64$, $p < 0.001$, $\eta_p^2 = 0.052$] and high domain slope [$M_{female} = -3.448$, $SD_{female} = 1.161$, $M_{male} = -4.347$, $SD_{male} = 1.760$, $F(1,212) = 15.51$, $p < 0.001$, $\eta_p^2 = 0.068$] with increased values indicating flatter spectra in females. The high domain intercept showed a consistent increase in female subjects [$F(1,212) = 22.988$, $p < 0.001$, $\eta_p^2 = 0.098$] as well. Furthermore, the slope difference between the low and high domain was significantly higher in males [$F(1212) = 13.899$, $p < 0.001$, $\eta_p^2 = 0.062$]. Considering the oscillatory component, the HF peak was more prominent in females [$F(1210) = 20.451$, $p < 0.001$, $\eta_p^2 = 0.089$] (Figs. 2 and 3).

3.4. Relationship to sleep macrostructure indicators

In the following, the effect of sleep structure on the spectral parameters was examined. WASO correlated negatively with the spectral intercept in both low [$r = -0.290$] and high [$r = -0.270$] domains, N1 percentage was also anticorrelated with the high domain intercept [$r = -0.298$], while R percentage showed positive association with the low domain intercept [$r = 0.303$], see Fig. 4.

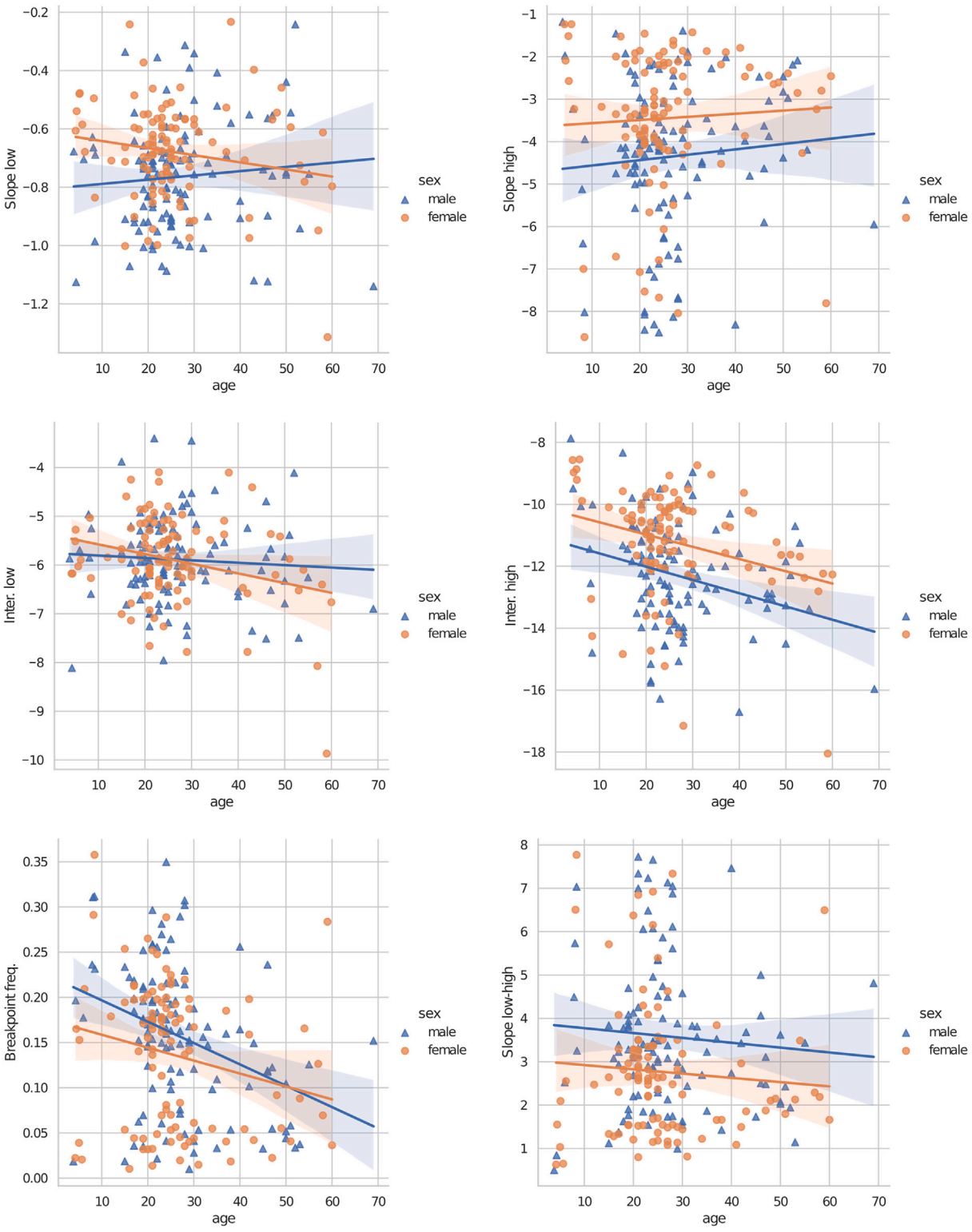

Fig. 2. ANCOVA plots of the fractal parameters. Significant effects of age were found in the high domain intercept ($F(1212) = 19.107$, $p < 0.001$, $\eta_p^2 = 0.083$, middle right) and breaking point frequency ($F(1206) = 18.08$, $p < 0.001$, $\eta_p^2 = 0.022$, bottom left), effects of sex were observed in both low domain slope ($F(1,212) = 11.64$, $p < 0.001$, $\eta_p^2 = 0.052$, top left) and high domain slope ($F(1,212) = 15.51$, $p < 0.001$, $\eta_p^2 = 0.068$, top right), high domain intercept ($F(1,212) = 22.988$, $p < 0.001$, $\eta_p^2 = 0.098$, middle right) and slope difference ($F(1212) = 13.899$, $p < 0.001$, $\eta^2 p_{=}0.062$, bottom right). (N = 215 subjects, 122 females).

In order to take into account the unequal temporal distribution of sleep stages throughout the night, in a first approach we divided a night into four equal quartiles and calculated the proportion of a sleep stage per quartile, which exhibited expected effects like late-night REM dominance, however no significant correlations were found with the spectral parameters. In another approach the mean time of occurrence per each

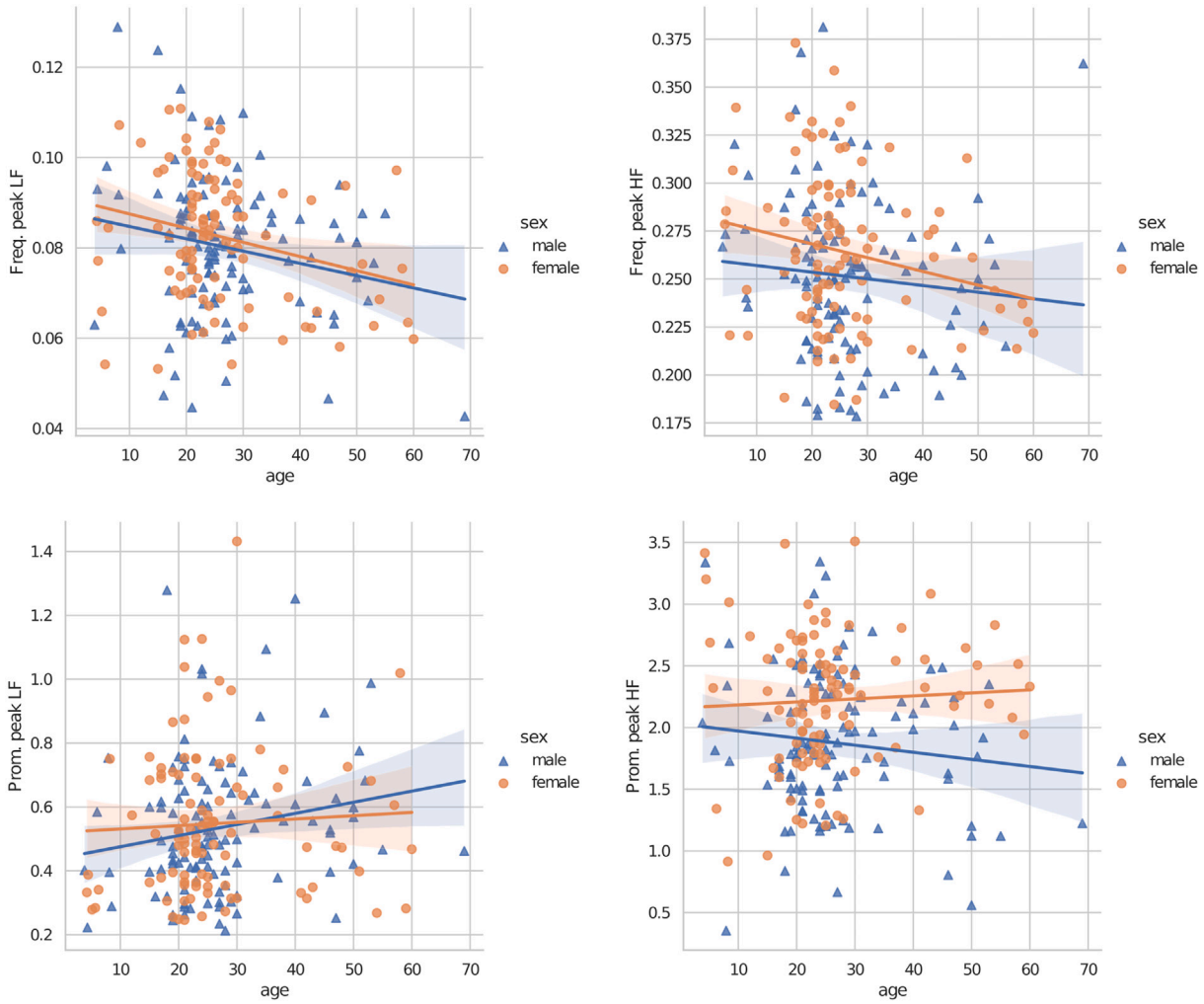

Fig. 3. ANCOVA plot of oscillatory parameters, significant effects of age in the LF peak frequency ($F(1206) = 11.502$, $p < 0.001$, $\eta_p^2 = 0.053$, top left) and sex in the HF peak prominence ($F(1, 212) = 22.988$, $p < 0.001$, $\eta_p^2 = 0.098$, bottom right). (N = 215 subjects, 122 females).

sleep stage was calculated, and these didn't show any association with the spectral parameters either.

3.5. Relationship to classical HRV markers

In order to assess which of our model parameters account for the individual differences in classical HRV measures, a multiple linear regression was implemented by considering each classical HRV marker as a dependent variable, and the fractal, oscillatory, then all spectral parameters as predictors. As both the classical HRV indicators are derived from the same power-spectra as the fitted fractal and oscillatory parameters, it is expected that there is an association between them, however, this analysis points out that most of the variance in the traditional band powers is present due to changes in the fractal parameters, and not of oscillatory nature. Traditional bands are defined around specific frequencies of well-known oscillatory processes (respiratory sinus arrhythmia, Mayer-waves), however, in all cases, total band power, LF and HF band power as well as the LF/HF ratio, a substantial amount of the variance in the traditional, band-limited spectral variables was explained by changes in the fractal parameters, see Table 3.

4. Discussion

Fractal spectra are ubiquitous in natural time series, including physiological rhythms and fluctuations. Former studies described the power law scaling of heart rate fluctuation spectra [16], revealing the physiological and cardiological relevance of the spectral parameters [2]. Moreover, sleep-associated heart rate was shown to characterize sleep quality and health [29]. Last, but not least, indirect evidence suggests the bi-fractal nature of human heart rate, characterized by different parameters in different frequency ranges [12,22]. Here we implemented a novel approach in determining sleep-related heart rate variation spectra with the aim of explicitly targeting a broken power law model-type description of the periodograms reflecting cardiac autonomic modulation in humans. As the two-slope model provided a more accurate description of the fractal spectra (also reflected by reduced Akaike information criteria), it evidenced the presence of a significant breaking point in the power-spectrum, which also carried physiological significance. Findings replicate and specify some of the assertions on the relatedness of sleep quality and the autonomic modulation of heart rate.

The piecewise linear regression approach applied to the fractal spectra of equidistantly resampled RR-series revealed novel spectral parameters of heart rate variability, which are related to, but not equivalent to the well-known frequency domain HRV measures of the band-limited type (e.g., total, LF, HF, power or LF/HF ratio). Consequently, some general comparisons can be made with the literature to interpret and confirm our results based on the aforementioned novel parameters.

Our finding of a significant intercept reduction in the high frequency domain with aging coheres with the age-related nocturnal HRV

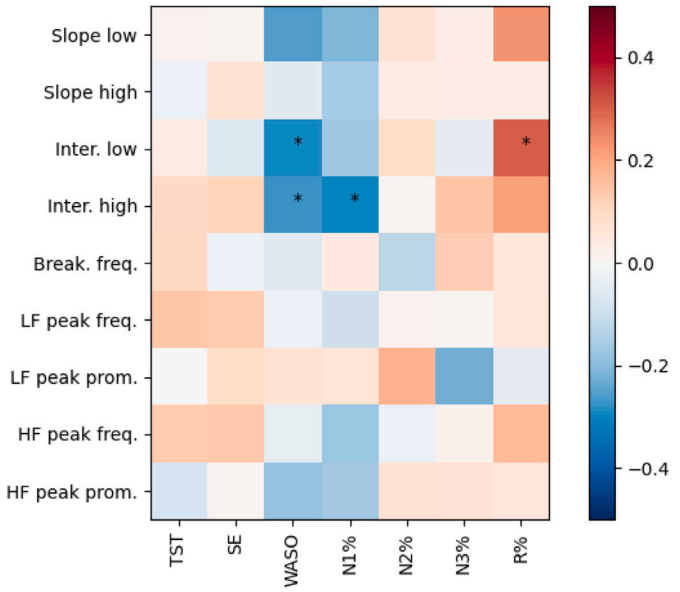

Fig. 4. Pearson correlation matrix of the spectral parameters and the sleep macrostructure indicators, significant relationships marked with "*", Bonferroni-Holm corrected ($\alpha = 0.005$). (TST - total sleep time, SE - sleep efficiency, WASO - wake after sleep onset, and sleep stage duration percentages).

Table 3
Variance of classical HRV indicators (columns) explained by groups of spectral parameters (rows), R^2 values of multiple linear regression tests. The spectral parameters were grouped as Fractal: low and high domain slope, low domain intercept, breaking point frequency; Oscillatory: peak frequency and prominence in the LF and HF bands; All: both fractal and oscillatory parameters.

Covariates	HRV (total)	LF power	HF power	LF/HF
Fractal	0.834	0.705	0.675	0.509
Oscillatory	0.086	0.131	0.115	0.303
All	0.838	0.862	0.704	0.738

attenuation indicating decreased adaptability [14,23]. Furthermore, published results indicate that age primarily affects the higher end of the spectrum [21], a finding that parallels the age-relatedness of the respective fractal parameters in our current study. Taken together with the new observation that the breaking point frequency also showed age-related reduction, and that there were no significant changes in the spectral slopes or peak prominences with age, we propose that the reduction of the total HRV power with aging can be explained by a shift in the broken power-law toward lower frequencies.

Looking at known sex differences in HRV [17], the attenuation of total HRV power in females compared to males is not obviously reflected in our results, however greater HF power supports our findings of increased high domain intercepts and HF peak prominences in females, increased LF/HF ratios are aligned with the flatter spectral slopes in both domains in our model.

As the dynamics of sleep and cardiac regulation are tied together by modulations in the ANS, HRV is also an indicator of sleep quality, being reduced in improper sleep [9,25,27], which confirms our results that more fragmented sleep is associated with an overall decrease in HRV power, as both the low and high domain intercepts showed significant anticorrelation with WASO duration. Furthermore, REM sleep is known to increase sympathetic tone, which is considered to be reflected by LF power increase [8], overlapping with the positive correlation between our low domain intercept and REM sleep percentage. Note that longer episodes of REM sleep can also be associated with quality sleep, as REM becomes more prominent with the dissipation of homeostatic sleep pressure. Consequently, the link between sleep and cardiac regulation could be utilized. On the one hand, while within-stage HRV measurements are known to be stable indicators [15], overnight variability measures are correlated with aspects of sleep structure, allowing for the assessment of sleep quality from heart rate data. On the other hand, in the future polysomnographic recordings might also provide data for automated cardiovascular health screenings.

Distinct oscillations were found in almost all cases in the LF and HF bands in the whitened oscillatory spectra. In addition the mean breaking point frequency in the fractal component was close to the 0.15 Hz boundary separating the two bands, which indicates the validity of splitting the two time scales, the variance and the discovered age effect on the breaking point frequency advise against setting a fixed boundary for the low and high frequency bands. An opposite-direction age-related change in the spectral breaking-point was found before in 24-hour HRV analysis [26], the frequency location of the breaking-point was significantly lower ($\approx 0.001\ Hz$), thus not meaningfully in the frequency range we covered. It is to be noted that in 24-hour recordings wake periods dominate, including food intake, physical and psychological activities, which require significant autonomic adaptation, while during sleep subjects were in recumbent position, void of external stimuli. It was hypothesized that the breaking-point is present in the spectrum as the heart rate signal is a superposition of two $1/f$-type noises with different slopes: one representing faster baseline fluctuations in the heart rate, the other being a slower, adaptive process. The breaking-point demarcates two time-scales in both cases, the exact underlying generating mechanisms are unclear, whether it is a physiological boundary, or a consequence of nested, multi-fractal nature of autonomic regulatory processes.

The novelty of our method lies in its ability to describe the complete frequency-domain landscape of HRV in a single model, in contrast to traditional metrics that are based on fixed frequency bands, furthermore it can differentiate between oscillatory and fractal changes. In the present study only the LF and HF bands were covered due to the limited duration of the ECG recordings, however the model is easily extendable to the VLF or ULF domains, given proper data. One limitation of our approach arises due to the common trade-off of spectral techniques, as the covered frequency range is wide, the temporal resolution is poor, so a single set of parameters characterizes the whole night. As such, the analysis of short-term effects, like stage-specific autonomic changes for example remains only correlational.

Most of the power variance was explained by aperiodic spectral parameters, while age and sex effects were attributed also to fractal parameters in greater numbers, so we propose that the changes occurring in the fractal component of the HRV spectra dominate these effects, in contrast to oscillations, and have to be considered in further studies.

CRediT authorship contribution statement

Bence Schneider: Writing – original draft, Visualization, Methodology, Conceptualization. **Martin Dresler:** Supervision, Investigation. **Ferenc Gombos:** Resources, Data curation. **Ilona Kovács:** Resources, Data curation. **Róbert Bódizs:** Writing – review & editing, Supervision, Data curation, Conceptualization.

Ethics in publishing statement

I testify on behalf of all co-authors that our article submitted follows ethical principles in publishing.

All authors agree that:

This research presents an accurate account of the work performed, all data presented are accurate and methodologies are detailed enough to permit others to replicate the work.

This manuscript represents entirely original work, and if the work and/or words of others have been used, they have been appropriately cited or quoted and permission has been obtained where necessary.

This material has not been published in whole or in part elsewhere.

The manuscript is not currently being considered for publication in another journal.

That generative AI and AI-assisted technologies have not been utilized in the writing process or if used, their use has been disclosed in the manuscript and a statement will appear in the published work.

That generative AI and AI-assisted technologies have not been used to create or alter images unless specifically used as part of the research design where such use must be described in a reproducible manner in the methods section.

All authors have been personally and actively involved in substantive work leading to the manuscript and will hold themselves jointly and individually responsible for its content.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered potential competing interests:

Bence Schneider reports that financial support was provided by University Research Scholarship (2024-2.1.1-EKÖP-2024-0004). If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

Supported by the University Research Scholarship (2024-2.1.1-EKÖP-2024-0004), as well as the Thematic Excellence (TKP2021-EGA-25 and TKP2021-NKTA- 47) Programmes of the Ministry for Culture and Innovation from the source of the National Research, Development and Innovation Fund, Hungary. It was made in the framework of the PPKE-BTK-KUT-23-1 project, with the support and funding provided by the Faculty of Humanities and Social Sciences of Pázmány Péter Catholic University.

References

[1] A.Z. Alrosan, G.B. Heilat, K. Alrosan, A.A. Aleikish, A.N. Rabbaa, A.M. Shakhatreh, E.M. Alshalout, E.M. Al Momany, Autonomic brain functioning and age-related health concerns, Current Research in Physiology 7 (2024) 100123, https://doi.org/10.1016/j.crphys.2024.100123

[2] J.T. Bigger, R.C. Steinman, L.M. Rolnitzky, J.L. Fleiss, P. Albrecht, R.J. Cohen, Power law behavior of RR-interval variability in healthy middle-aged persons, patients with recent acute myocardial infarction, and patients with heart transplants, Circulation 93 (1996) 2142–2151, https://doi.org/10.1161/01.cir.93.12.2142

[3] G.E. Billman, The LF/HF ratio does not accurately measure cardiac sympatho-vagal balance, Front. Physiol. 4 (2013), https://doi.org/10.3389/fphys.2013.00026

[4] R. Bódizs, F. Gombos, P.P. Ujma, S. Szakadát, P. Sándor, P. Simor, A. Pótári, B.N. Konrad, L. Genzel, A. Steiger, M. Dresler, I. Kovács, The hemispheric lateralization of sleep spindles in humans, Sleep Spindles and Cortical Up States 1 (2017) 42–54, https://doi.org/10.1556/2053.01.2017.002

[5] H. ChuDuc, K. NguyenPhan, D. NguyenViet, A review of heart rate variability and its applications, APCBEE Procedia 7 (2013) 80–85, https://doi.org/10.1016/j.apcbee.2013.08.016

[6] M.A. Colombo, M. Napolitani, M. Boly, O. Gosseries, S. Casarotto, M. Rosanova, J.F. Brichant, P. Boveroux, S. Rex, S. Laureys, M. Massimini, A. Chieregato, S. Sarasso, The spectral exponent of the resting EEG indexes the presence of consciousness during unresponsiveness induced by propofol, xenon, and ketamine, Neuroimage 189 (2019) 631–644, https://doi.org/10.1016/j.neuroimage.2019.01.024

[7] T. Donoghue, M. Haller, E.J. Peterson, P. Varma, P. Sebastian, R. Gao, T. Noto, A.H. Lara, J.D. Wallis, R.T. Knight, A. Shestyuk, B. Voytek, Parameterizing neural power spectra into periodic and aperiodic components, Nat. Neurosci. 23 (2020) 1655–1665, https://doi.org/10.1038/s41593-020-00744-x

[8] S. Elsenbruch, M.J. Harnish, W.C. Orr, Heart rate variability during waking and sleep in healthy Males and females, Sleep 22 (1999) 1067–1071, https://doi.org/10.1093/sleep/22.8.1067

[9] C. da Estrela, J. McGrath, L. Booij, J.P. Gouin, Heart rate variability, sleep quality, and depression in the context of chronic stress, Ann. Behav. Med. 55 (2020) 155–164, https://doi.org/10.1093/abm/kaaa039

[10] I. Gkioulekas, L.G. Papageorgiou, Piecewise regression through the Akaike information criterion using mathematical programming, IFAC-Pap. 51 (2018) 730–735, https://doi.org/10.1016/j.ifacol.2018.09.168

[11] C. Iber, S. Ancoli-Israel, A. Chesson, S. Quan, The AASM Manual for the Scoring of Sleep and Associated Events: Rules, Terminology and Technical Specification, American Academy of Sleep Medicine, 2007.

[12] P.C. Ivanov, L.A.N. Amaral, A.L. Goldberger, S. Havlin, M.G. Rosenblum, Z.R. Struzik, H.E. Stanley, Multifractality in human heartbeat dynamics, Nature 399 (1999) 461–465, https://doi.org/10.1038/20924

[13] C.F. Jekel, G. Venter, PWLF: a Python library for fitting 1D continuous piecewise linear functions, 2019, https://github.com/cjekel/piecewise_linear_fit_py.

[14] T. Kentta, M. Karsikas, A. Rantanen, H. Kinnunen, H. Koskimaki, Age, sex and underlying heart rate as determinants of nocturnal heart rate variability among wearable smart ring users, Eur. Heart J. 41 (2020), https://doi.org/10.1093/ehjci/ehaa946.3463

[15] E.M. Kerkering, I.M. Greenlund, J.A. Bigalke, G.C.L. Migliaccio, C.A. Smoot, J.R. Carter, Reliability of heart rate variability during stable and disrupted polysomnographic sleep, American Journal of Physiology-Heart and Circulatory Physiology 323 (2022) H16–H23, https://doi.org/10.1152/ajpheart.00143.2022

[16] M. Kobayashi, T. Musha, 1/f fluctuation of heartbeat period, IEEE Trans. Biomed. Eng. BME-29 (1982) 456–457, https://doi.org/10.1109/tbme.1982.324972

[17] J. Koenig, J.F. Thayer, Sex differences in healthy human heart rate variability: a meta-analysis, Neuroscience. Biobehavioral Reviews 64 (2016) 288–310, https://doi.org/10.1016/j.neubiorev.2016.03.007

[18] C. Maschke, C. Duclos, A.M. Owen, K. Jerbi, S. Blain-Moraes, Aperiodic brain activity and response to anesthesia vary in disorders of consciousness, Neuroimage 275 (2023) 120154, https://doi.org/10.1016/j.neuroimage.2023.120154

[19] O. Monfredi, E.G. Lakatta, Complexities in cardiovascular rhythmicity: perspectives on circadian normality, ageing and disease, Cardiovasc. Res. 115 (2019) 1576–1595, https://doi.org/10.1093/cvr/cvz112

[20] M. Nagai, S. Hoshide, K. Kario, Sleep duration as a risk factor for cardiovascular disease- a review of the recent literature, Current Cardiology Reviews 6 (2010) 54–61, https://doi.org/10.2174/157340310790231635

[21] F. Olivieri, L. Biscetti, L. Pimpini, G. Pelliccioni, J. Sabbatinelli, S. Giunta, Heart rate variability and autonomic nervous system imbalance: potential biomarkers and detectable hallmarks of aging and inflammaging, Ageing Res. Rev. 101 (2024) 102521, https://doi.org/10.1016/j.arr.2024.102521

[22] C.K. Peng, S. Havlin, H.E. Stanley, A.L. Goldberger, Quantification of scaling exponents and crossover phenomena in nonstationary heartbeat time series, Chaos Interdiscip. J. Nonlinear Sci. 5 (1995) 82–87, https://doi.org/10.1063/1.166141

[23] M. REARDON, M. MALIK, Changes in heart rate variability with age, Pacing Clin. Electrophysiol. 19 (1996) 1863–1866, https://doi.org/10.1111/j.1540-8159.1996.tb03241.x

[24] A. Rechtschaffen, A. Kales, A Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Subjects, Brain Information Service/Brain Research Institute, University of California, Los Angeles, 1968, pp. 4.

[25] A. Sajjadieh, A. Shahsavari, A. Safaei, T. Penzel, C. Schoebel, I. Fietze, N. Mozafarian, B. Amra, R. Kelishadi, The association of sleep duration and quality with heart rate variability and blood pressure, Tanaffos 19 (2020) 135–143.

[26] S. Sakata, J. Hayano, S. Mukai, A. Okada, T. Fujinami, Aging and spectral characteristics of the nonharmonic component of 24-h heart rate variability, Am. J. Physiol.-Regul. Integr. Comp. Physiol. 276 (1999) R1724–R1731, https://doi.org/10.1152/ajpregu.1999.276.6.R1724. PMID: 10362753.

[27] J. Schlagintweit, N. Laharnar, M. Glos, M. Zemann, A.V. Demin, K. Lederer, T. Penzel, I. Fietze, Effects of sleep fragmentation and partial sleep restriction on heart rate variability during night, Sci. Rep. 13 (2023), https://doi.org/10.1038/s41598-023-33013-5

[28] B. Schneider, O. Szalárdy, P.P. Ujma, P. Simor, F. Gombos, I. Kovács, M. Dresler, R. Bódizs, Scale-free and oscillatory spectral measures of sleep stages in humans, Front. Neuroinformatics 16 (2022), https://doi.org/10.3389/fninf.2022.989262

[29] P.K. Stein, Y. Pu, Heart rate variability, sleep and sleep disorders, Sleep Med. Rev. 16 (2012) 47–66, https://doi.org/10.1016/j.smrv.2011.02.005

[30] M.P. Tarvainen, J.P. Niskanen, J.A. Lipponen, P.O. Ranta-Aho, P.A. Karjalainen, Kubios HRV – heart rate variability analysis software, Comput. Methods Programs Biomed. 113 (2014) 210–220, https://doi.org/10.1016/j.cmpb.2013.07.024

[31] E. Tobaldini, L. Nobili, S. Strada, K.R. Casali, A. Braghiroli, N. Montano, Heart rate variability in normal and pathological sleep, Front. Physiol. 4 (2013), https://doi.org/10.3389/fphys.2013.00294

[32] P. Virtanen, R. Gommers, T.E. Oliphant, M. Haberland, T. Reddy, D. Cournapeau, E. Burovski, P. Peterson, W. Weckesser, J. Bright, S.J. van der Walt, M. Brett, J. Wilson, K.J. Millman, N. Mayorov, A.R.J. Nelson, E. Jones, R. Kern, E. Larson, C.J. Carey, A. Polat, Y. Feng, E.W. Moore, J. VanderPlas, D. Laxalde, J. Perktold, R. Cimrman, I. Henriksen, E.A. Quintero, C.R. Harris, A.M. Archibald, A.H. Ribeiro, F. Pedregosa, P. van Mulbregt, A. Vijaykumar, A.P. Bardelli, A. Rothberg, A. Hilboll, A. Kloeckner, A. Scopatz, A. Lee, A. Rokem, C.N. Woods, C. Fulton, C. Masson, C. Häggström, C. Fitzgerald, D.A. Nicholson, D.R. Hagen, D.V. Pasechnik, E. Olivetti, E. Martin, E. Wieser, F. Silva, F. Lenders, F. Wilhelm, G. Young, G.A. Price, G.L. Ingold, G.E. Allen, G.R. Lee, H. Audren, I. Probst, J.P. Dietrich, J. Silterra, J.T. Webber, J. Slavič, J. Nothman, J. Buchner, J. Kulick, J.L. Schönberger, J.V. de Miranda Cardoso, J. Reimer, J. Harrington, J.L.C. Rodríguez, J. Nunez-Iglesias, J. Kuczynski, K. Tritz, M. Thoma, M. Newville, M. Kümmerer, M. Bolingbroke, M. Tartre, M. Pak, N.J. Smith, N. Nowaczyk, N. Shebanov, O. Pavlyk, P.A. Brodtkorb, P. Lee, R.T. McGibbon, R. Feldbauer, S. Lewis, S. Tygier, S. Sievert, S. Vigna, S. Peterson, S. More, T. Pudlik, T. Oshima, T.J. Pingel, T.P. Robitaille, T. Spura, T.R. Jones, T. Cera, T. Leslie, T. Zito, T. Krauss, U. Upadhyay, Y.O. Halchenko, Y. Vázquez-Baeza, SciPy 1.0: fundamental algorithms for scientific computing in Python, Nat. Methods 17 (2020) 261–272, https://doi.org/10.1038/s41592-019-0686-2

[33] H. Wen, Z. Liu, Separating fractal and oscillatory components in the power spectrum of neurophysiological signal, Brain Topogr. 29 (2015) 13–26, https://doi.org/10.1007/s10548-015-0448-0

[34] Y. Yamamoto, R.L. Hughson, On the fractal nature of heart rate variability in humans: effects of data length and beta-adrenergic blockade, Am. J. Physiol.-Regul. Integr. Comp. Physiol. 266 (1994) R40–R49, https://doi.org/10.1152/ajpregu.1994.266.1.r40