

Supplementary Information for

Universal rhythmic architecture uncovers two modes of neural dynamics

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- Supplementary Text
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- Supplementary Figures S1 to S6
- Supplementary References

Supplementary Text

Parametrical effects on rhythmicity measures

As mentioned in the Lagged Angle Vector Index (LAVI) section of methods, the founding principle underlying the lagged coherence (LC) analysis is that “real” oscillations are repetitive. Therefore, their periodic waveforms should allow for the prediction of future phases based on the phase of the present one. Based on this principle, Fransen and colleagues¹ defined *rhythmicity* as “the consistency of the phase relations between time points that are separated by some interval (lag)”. Practically, rhythmicity (computed with LC) measures the predictability of future phases based on the current one: the better future phases can be predicted, the more rhythmic the signal. Fransen et al also noted, that LC varies as a function of both frequency and lag. LC peaks at frequencies corresponding to “canonical bands” (Fig. 1), and decreases with increasing lag (fig. S5A, example from 60 sec recordings from one participant in dataset III).

Based on this dependence of LC on both frequency and lag, several studies^{1–3} quantified how oscillatory an activity in a specific band is based on the “lifetime” of the LC. That is, for how long (i.e., for how many lags) does the LC exceed a threshold. However, two difficulties arise when adopting this approach: first, the threshold has to be calculated for each frequency separately, which undermines inter-frequency comparisons². Second, it requires computing the LC for numerous lags (e.g. 0 to 20 cycles in steps of 0.1, summing to 201 lags² or 2 to 7 cycles, summing to 51 lags³). This makes LC computationally very intensive.

Looking for a computationally fast way to utilize rhythmicity to define oscillatory bands, we investigated how different parameters affect LAVI. First, we noticed that the dynamic range of the rhythmicity is lower in short (≤ 1 cycle) and long (≥ 3 cycles) lags compared to lags between 1 and 2 cycles (fig. S5B). This effect is due to a ceiling effect in short lags and a floor effect in long lags. Importantly, the median (across frequencies) is lag-dependent and is highly stable across participants (fig. S5C, 60 sec EEG from N=127 participants, datasets I-IV).

Another parameter that affects the median of LAVI is the duration of the sliding window used to calculate the time-frequency transform. We used Wavelet transform, hence this parameter is reflected in the length of the Wavelet, measured in cycles per frequency. As expected, a wider Wavelet leads to higher assessed rhythmicity (Fig. S5D), since a longer window enforces greater phase consistency by design. This effect reflects an **analytic property** of the wavelet transform rather than a physiological signal. However, our approach does not rely on absolute LAVI values, but rather on **within-subject, within-analysis relative comparisons**, such as deviations from the median at each frequency. Based on the finding that the LAVI median is highly stable across participants (e.g., standard deviation of 0.01, when using lag=1.5 cycles and Wavelet width =5 cycles), and depends on parameters controlled by the experimenter, we developed an approach to assess band borders based on one lag. That is, instead of measuring how rhythmicity changes over time relative to a baseline time-point, we measure how rhythmicity in each frequency changes relative to the median, in one time-point. We found that using a lag of 1.5 cycles and Wavelet of 5 cycles (arrows in fig S5C and S5D) allows estimation of rhythmicity that is computationally efficient, stable across participants, and offers good dynamic range (median of 0.4, that allows frequency to go above and below the median, without ceiling and floor effects).

Importantly, the median of LAVI depends on the lag and wavelet width, regardless of its source. This can be demonstrated with analysis of surrogate (random) data with spectral characteristics similar to the characteristic of neurophysiological data. In general, the power of the electrophysiological signal is inversely proportional to the frequency, or $P = 1/f^\alpha$, with P designating Power and the fractal α

represent how steeply the power decreases. In brain signals, the fractal (also called the aperiodic component) is predominantly between 0.5 and 2, which is representative for signals dubbed “pink noise” (in the data analysed for this manuscript, out of 1150 recording sites, 82.4% had $0.5 \leq \alpha \leq 2$, fig S5E). Leveraging this feature, we characterized the rhythmicity of data with similar pink-noise characteristics as our recorded data, but with shuffled (that is, random) phases, using the IAAFT algorithm⁴⁻⁷. Starting with raw EEG data from participants, we calculated the aperiodic component of the signal by fitting a power function (fig. S5F). Then, we used the fit as the spectrum input to the IAAFT algorithm (fig. S5G). Finally, we computed the rhythmicity (LAVI) of both the original and surrogate data. As shown in fig. S5H, the rhythmicity curves of both “real” and surrogate data share the same median (~ 0.4 , when using lag = 1.5 cycles and Wavelet width = 5 cycles). However, while the “real” data exhibits fluctuations with distinct peaks and troughs, the surrogate (“pink”) data fluctuates much less. We further utilized this finding to define noise levels of per-subject LAVI, treating the median as the baseline and matched pink-noise fluctuations as noise-floor. This approach allows statistical inference of each band (see ABBA in the main text, Methods).

Notably, fluctuations in LAVI can be affected by how oscillatory or bursty the data is in specific frequencies, but also from other parameters. These parameters can be exploited to define the noise-floor. First, the higher the aperiodic exponent (α), the higher the noise, especially in low frequencies (fig. S5I). Second, noise level decreases (and in fact, accuracy increases) with increased sampling frequency. This effect becomes more prominent with higher frequencies, since the sampling frequency defines how many samples are there in each cycle, and hence the range of possible phases that can be measured (fig. S5J). Finally, the total duration of the recorded session affects noise levels in low frequencies (fig. S5K). Based on this parameterization, one can generate a table containing expected noise levels based on given aperiodic exponent, sampling frequency, and session duration. Generating such table requires simulating at least 20 repetitions of pink-noise for each parameter combination (to allow bootstrapping with $\alpha=0.05$). This process can be time consuming, but carries the advantage of after being done once, the table can be used with all datasets with similar experimental conditions, thus speed up analysis. We make the table created for this manuscript, along with the code used to generate it, publicly available.

Supplementary Table S1.

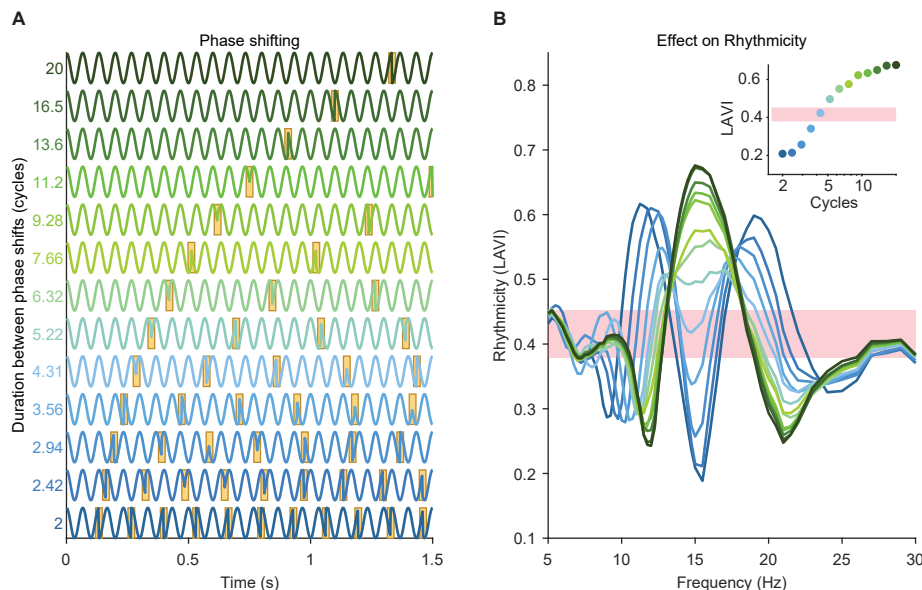
Fig.	Measure	Groups	Statistical test	Test statistic	Deg. of freedom	p-value (corrected)	Effect size	Post-hoc comparisons	Bayes Factor
3B	Burst duration (power)	Low-High rhythmicity	ANOVA	F = 36.30	3,140	2.04E-17 (6.1E-17)	$\eta^2 = 0.437$	Low-high: 9.8E-18 Low-pink: 0.030 High-pink: 1.6E-10 Pink-pink: 0.447	3.36E+14
3C	Burst duration (WTPL)	Low-High rhythmicity	ANOVA	F = 76.01	3,140	3.11E-29 (1.9E-28)	$\eta^2 = 0.620$	Low-high: 1.0E-30 Low-pink: 1.3E-08 High-pink: 2.4E-16 Pink-pink: 0.665	1.31E+26
3D	Burst rate	Low-High rhythmicity	ANOVA	F = 33.21	3,140	2.83E-16 (5.7E-16)	$\eta^2 = 0.416$	Low-high: 2.7E-17 Low-pink: 3.3E-04 High-pink: 2.0E-10 Pink-pink: 0.390	2.58E+13
3E	Occupancy	Low-High rhythmicity	ANOVA	F = 3.76	3,140	0.012 (0.015)	$\eta^2 = 0.075$	Low-high: 0.231 Low-pink: 0.400 High-pink: 2.6E-03 Pink-pink: 7.6E-03	1.401
3F	Power (relative threshold)	Low-High rhythmicity	ANOVA	F = 18.31	3,140	4.46E-10 (6.7E-10)	$\eta^2 = 0.282$	Low-high: 5.0E-03 Low-pink: 4.2E-05 High-pink: 1.9E-06 Pink-pink: 0.036	2.4E+12
3G	Band consistency	Low-High rhythmicity	ANOVA	F = 1.86	3,140	0.139 (0.139)	$\eta^2 = 0.038$	Low-high: 0.076 Low-pink: 0.758 High-pink: 0.028 Pink-pink: 0.455	0.134
4A	Frequency- δ/θ	Dataset	ANOVA	F = 2.50	5,172	0.033 (0.09)	$\eta^2 = 0.080$	I-IV: 0.043 II-III: 0.021 II-IV: 0.001	0.413
4A	Frequency- β_2	Dataset	ANOVA	F = 2.92	5,172	0.015 (0.059)	$\eta^2 = 0.078$	I-IV: 0.030 I-V: 0.003 III-V: 0.016 V-VI: 0.009	0.748
4A	Frequency- γ_1	Dataset	ANOVA	F = 5.12	5,172	2.1E-04 (0.002)	$\eta^2 = 0.132$	I-IV: 0.046 I-V: 1.8E-05 II-V: 1.7E-03 III-V: 6.1E-05 IV-V: 0.032 V-VI: 3.2E-04	53.664
4D	Frequency- δ/θ	Region	ANOVA	F = 3.52	5,313 (only sig.)	4.1E-03 (0.007)	$\eta^2 = 0.053$	Occ-VT: 0.003 Occ-Par: 0.001 Occ-PFC: 0.005 Occ-LT: 0.038 Par-SM: 0.021	1.271
4D	Frequency- θ/α	Region	ANOVA	F = 4.51	5, 626 (only sig.)	4.8E-04 (9.6E-04)	$\eta^2 = 0.035$	Occ-VT: 9.4E-06 Occ-Par: 0.002 Occ-SM: 0.025 VT-PFC: 0.034 VT-LT: 0.005	4.791
4D	Frequency- α	Region	ANOVA	F = 11.61	5, 715 (only sig.)	8.5E-11 (6.8E-10)	$\eta^2 = 0.075$	Occ-VT: 4.7E-13 Occ-Par: 4.1E-03 Occ-PFC: 3.9E-04 Occ-SM: 2.0E-05 Occ-LT: 1.8E-05 VT-Par: 1.7E-04 VT-LT: 0.031	5.08E+07
4D	Frequency- β_1	Region	ANOVA	F = 5.93	5, 641 (only sig.)	2.3E-05 (6.5E-05)	$\eta^2 = 0.044$	Occ-VT: 6.3E-04 Occ-PFC: 3.8E-05 Occ-SM: 3.1E-04 Occ-LT: 4.4E-04 VT-Par: 0.025 Par-PFC: 1.7E-03 Par-SM: 0.008	100.93

Fig.	Measure	Groups	Statistical test	Test statistic	Deg. of freedom	p-value (corrected)	Effect size	Post-hoc comparisons	Bayes Factor
								Par-LT: 0.017	
4D	Frequency- β_2	Region	ANOVA	F = 5.89	5, 650 (only sig.)	2.4E-05 (6.5E-05)	$\eta^2= 0.043$	Occ-VT: 1.6E-06 Occ-SM: 0.021 Occ-LT: 0.013 VT-Par: 2.5E-03 VT-PFC: 3.0E-04	114.29
4D	Frequency- γ_1	Region	ANOVA	F = 3.05	5, 518 (only sig.)	0.010 (0.014)	$\eta^2= 0.029$	VT-PFC: 0.010 Par-PFC: 5.4E-04 Par-SM: 8.1E-03 PFC-LT: 0.025	0.19
4G	Frequency- δ/θ	Region	ANOVA	F = 2.50	6,501 (only sig.)	0.022 (0.034)	$\eta^2= 0.029$	MF-LT: 0.024 LF-LT: 0.009 Ins.-LT: 0.006 Ins.-MT: 0.033	0.11
4G	Frequency- α	Region	ANOVA	F = 5.78	6, 726 (only sig.)	6.8E-06 (1.0E-04)	$\eta^2= 0.046$	MF-LF: 0.004 LF-Ins.: 0.004 LF-MP: 0.023 LF-LP: 1.8E-06 LF-LT: 3.5E-06 LF-MT: 1.0E-06	439.94
4G	Frequency- β_1	Region	ANOVA	F = 5.41	6, 726 (only sig.)	1.7E-05 (1.0E-04)	$\eta^2= 0.043$	MF-LF: 8.5E-04 LF-Ins.: 0.025 LF-MP: 0.010 LF-LP: 1.5E-06 LF-LT: 5.6E-06 LF-MT: 2.0E-05	159.91
4G	Frequency- β_2	Region	ANOVA	F = 3.93	6, 721 (only sig.)	7.2E-04 (1.9E-03)	$\eta^2= 0.032$	MF-LF: 4.3E-02 LF-LP: 4.7E-05 MP-LP: 0.024 LP-LT: 5.5E-04 LP-MT: 1.6E-02	2.94
4G	Frequency- γ_1	Region	ANOVA	F = 3.28	6, 707 (only sig.)	3.4E-03 (0.007)	$\eta^2= 0.027$	MF-LF: 5.0E-02 MF-LT: 2.1E-03 Ins.-LT: 0.010 MP-LT: 8.1E-03 LP-LT: 4.3E-04 LT-MT: 0.023	0.50
5B	Band frequency	Invasive – non-invasive	ANOVA-method	F = 0.3	1,5527	0.58	$\eta^2= 5.45E-5$		0.042
5D	Band frequency	Rat – Human	ANOVA-species	F = 0.05	1,336	0.83	$\eta^2=1.43E-4$		0.091
5F	Band frequency	Female - Male	ANOVA-sex	0.26	1,4414	0.611	$\eta^2=5.9E-05$		0.0231
6B	Band frequency	Age	Pearson correlation	$\rho =$ δ : -0.149 δ/θ : -0.040 θ : -0.208 θ/α : -0.228 α : -0.340 β_1 : -0.119 β_2 : -0.134 γ_1 : 0.015	n = δ : 253 δ/θ : 539 θ : 590 θ/α : 618 α : 618 β_1 : 618 β_2 : 612 γ_1 : 612	corrected δ: 0.024 δ/θ : 0.409 θ: 9.8E-07 θ/α: 4E-08 α: 2.9E-17 β_1: 5E-03 β_2: 2E-03 γ_1 : 0.715			
6B	Band rhythmicity magnitude	Age	Pearson correlation	$\rho =$ δ : 0.147 δ/θ : -0.058 θ : -0.051 θ/α : 0.057 α : -0.203 β_1 : 0.333 β_2 : -0.029 γ_1 : -0.012	n = δ : 253 δ/θ : 539 θ : 590 θ/α : 618 α : 618 β_1 : 618 β_2 : 612 γ_1 : 612	corrected δ : 0.052 δ/θ : 0.283 θ : 0.286 θ/α : 0.283 α: 1.5E-06 β_1:1.6E-16 β_2 : 0.543 γ_1 : 0.770			
6B	Band frequency	Age	ANOVA- δ	F = 1.95	6,244	0.074 (0.099)	$\eta^2= 0.046$		0.066

Fig.	Measure	Groups	Statistical test	Test statistic	Deg. of freedom	p-value (corrected)	Effect size	Post-hoc comparisons	Bayes Factor
6B	Band frequency	Age	ANOVA- δ/θ	F = 0.73	6,525	0.623 (0.712)	$\eta^2 = 0.0083$		5.37E-4
6B	Band frequency	Age	ANOVA- θ	F = 5.1	6,574	4E-5 (1.07E-4)	$\eta^2 = 0.05$	18-28 - 68-78: 3.4E-04 18-28 - 78-88: 8.1E-03 28-38 - 48-58: 0.031 28-38 - 58-68: 0.012 28-38 - 68-78: 5.0E-06 28-38 - 78-88: 6.8E-04 38-48 - 68-78: 5.6E-04 38-48 - 78-88: 0.022 48-58 - 68-78: 0.016 58-68 - 68-78: 0.046	55.3
6B	Band frequency	Age	ANOVA- θ/α	F = 6.8	6,604	5.34E-7 (2.14E-6)	$\eta^2 = 0.063$	18-28 - 48-58: 0.044 18-28 - 58-68: 0.031 18-28 - 68-78: 1.1E-03 18-28 - 78-88: 7.3E-04 28-38 - 48-58: 7.8E-03 28-38 - 58-68: 4.7E-03 28-38 - 68-78: 4.1E-05 28-38 - 78-88: 2.9E-05 38-48 - 48-58: 8.1E-03 38-48 - 58-68: 4.7E-03 38-48 - 68-78: 3.2E-05 38-48 - 78-88: 2.4E-05	4.78E+3
6B	Band frequency	Age	ANOVA- α	F = 13.73	6,604	1.18E-14 (9.45E-14)	$\eta^2 = 0.12$	18-28 - 48-58: 6.5E-04 18-28 - 58-68: 3.5E-06 18-28 - 68-78: 4.2E-08 18-28 - 78-88: 7.2E-08 28-38 - 48-58: 6.9E-04 28-38 - 58-68: 1.3E-06 28-38 - 68-78: 5.9E-09 28-38 - 78-88: 1.6E-08 38-48 - 48-58: 0.010 38-48 - 58-68: 4.4E-05 38-48 - 68-78: 3.0E-07 38-48 - 78-88: 6.6E-07 48-58 - 68-78: 0.012 48-58 - 78-88: 0.012	2.55E+11
6B	Band frequency	Age	ANOVA- β_1	F = 2.73	6,604	0.0125 (0.025)	$\eta^2 = 0.0264$	18-28 - 48-58: 0.047 18-28 - 58-68: 0.020 18-28 - 68-78: 7.4E-03 18-28 - 78-88: 7.3E-03 28-38 - 68-78: 0.020 28-38 - 78-88: 0.020	0.082
6B	Band frequency	Age	ANOVA- β_2	F = 2.27	6,598	0.035 (0.057)	$\eta^2 = 0.0223$		0.0223
6B	Band frequency	Age	ANOVA- γ_1	F = 0.56	6,598	0.762 (0.762)	$\eta^2 = 0.0056$		2.23E-4
6D	Burst duration	PD, Bands x On/Off med	ANOVA2-bands	F = 0.51	1,60	0.48	$\eta^2 = 0.009$		0.204
6D	Burst duration	PD, Bands x On/Off med	ANOVA2-medication	F = 10.59	1,60	0.0019	$\eta^2 = 0.154$	β_1 , off- β_1 , on: 0.0026 β_1 , off- β_2 , on: 0.007	14.875
6D	Burst duration	PD, Bands x On/Off med	ANOVA2-interaction	F = 1.605	1,60	0.21	$\eta^2 = 0.027$		0.456
6E	Burst rate	PD, Bands x On/Off med	ANOVA2-bands	F = 23.78	1,60	8.3E-6	$\eta^2 = 0.28$	β_1 , off- β_2 , off: 2.0E-03 β_1 , off- β_2 , on: 1.6E-03 β_1 , on- β_2 , off: 0.018 β_1 , off- β_2 , on: 0.015	2.83E+3
6E	Burst rate	PD, Bands x On/Off med	ANOVA2-medication	F = 0.33	1,60	0.56	$\eta^2 = 0.056$		0.18
6E	Burst rate	PD, Bands x On/Off med	ANOVA-2 interaction	F = 0.23	1,60	0.64	$\eta^2 = 0.004$		0.246

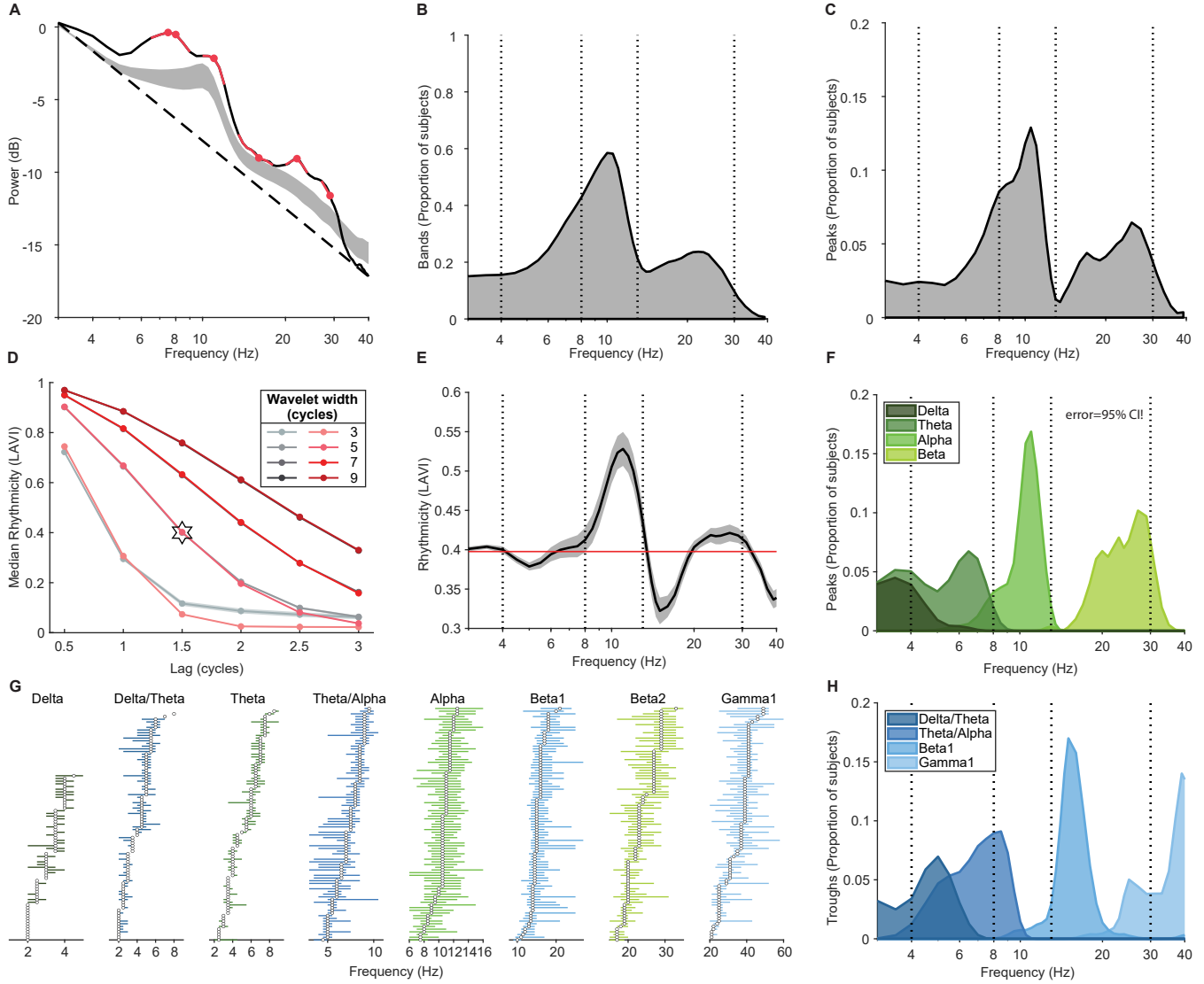
Statistical reporting table.

All tests are two-sided. Correction for multiple comparisons was performed with the false discovery rate according to the Benjamini-Hochberg algorithm. Post-hoc tests following ANOVA were performed with the Fisher's least significant difference procedure. Significant p values are presented in bold. Fig.: the figure panel in which the test is presented. Deg.: degrees.



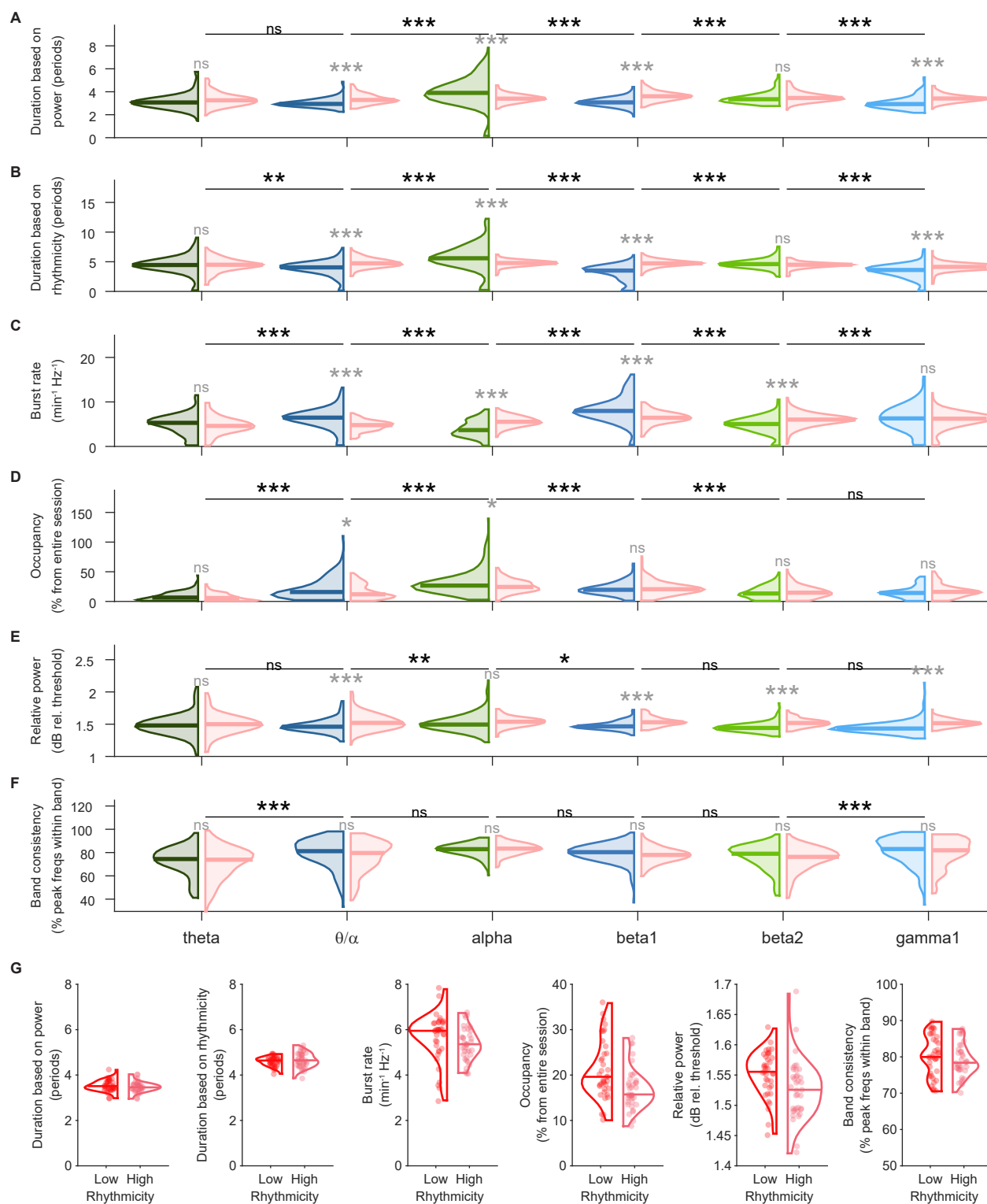
Supplementary Figure S1. The Lagged Angle Vector Index (LAVI) measures rhythmicity.

In each frequency, LAVI reflects how sustained the oscillation is over the session: sustained oscillations receive high rhythmicity values, while frequent phase shifts reduce LAVI. For direct demonstration of the effect of sustainability on LAVI, we flipped the sign of the phase of the 15 Hz component of pink-noise every set amount of cycles ranging from 2 to 20. (A) Simulated signal, filtered at 15 Hz, arranged from “ephemeral” (blue) to “rhythmic” (green). Phase-shifts are marked in gold. (B) The LAVI profile over frequencies. Colour of traces corresponds to (A). Pink shading corresponds to the noise, estimated as the minimal and maximal LAVI values of the pink-noise data (without filter weight adjustment at 15 Hz). Inset: LAVI values at the modulated frequency (15 Hz). The signal becomes more rhythmic than noise around four cycles. Note that increasing (decreasing) the rhythmicity in one band decreases (increases) rhythmicity in neighbouring bands. This can be caused by interference. However, peaks and troughs in physiological data are above and beyond this effect (for more details, see fig. S5). Source data are provided as a Source Data file.



Supplementary Figure S2. Band segregation using power and rhythmicity.

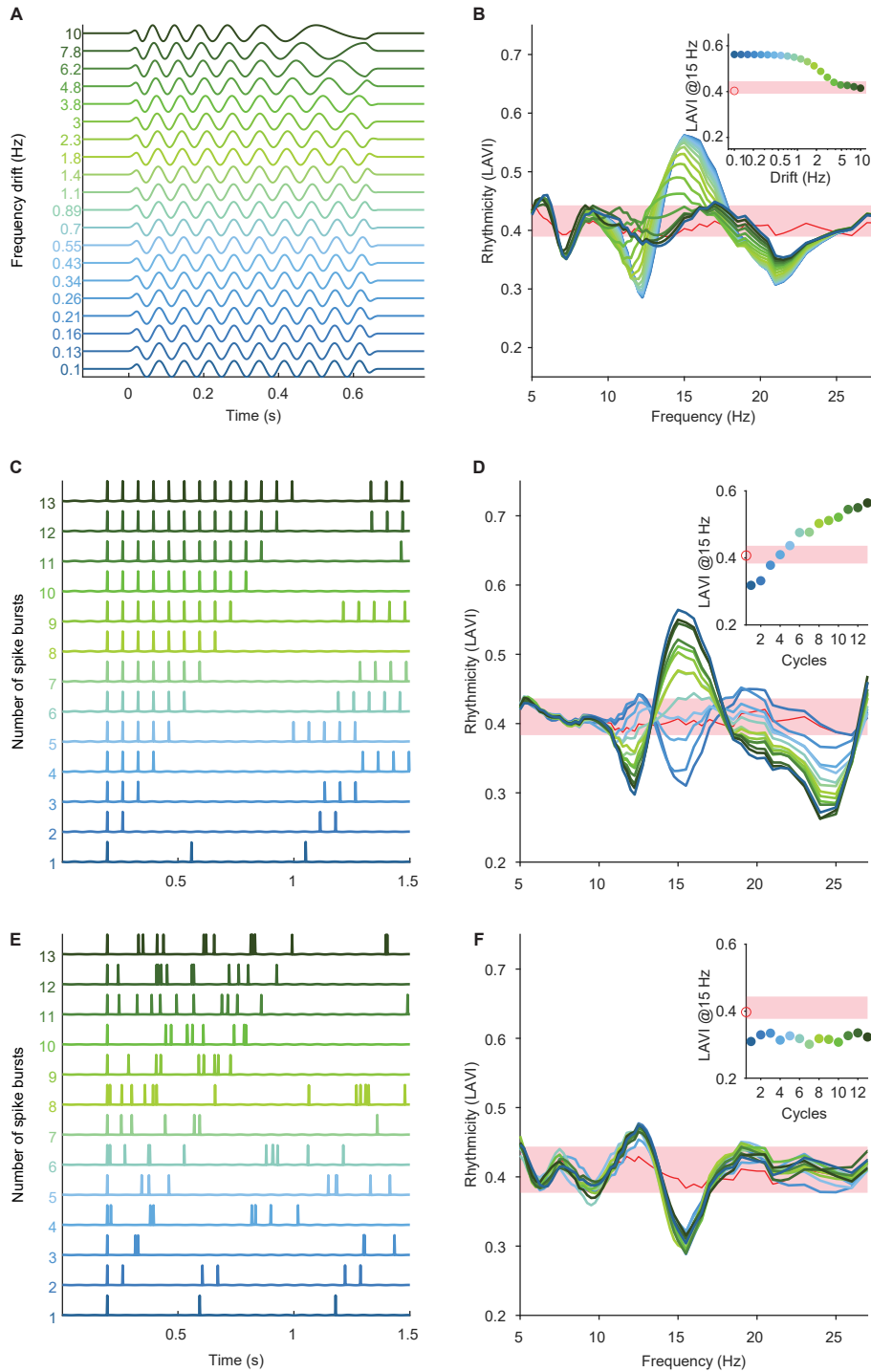
(A) Brainwave bands are commonly defined as bumps above the $1/f$ aperiodic component. Black trace: power spectrum of one subject (same as in Fig. 1). Dashed line: the $1/f$ fit. Pink: bands detected using an iterative Gaussian-fit algorithm (specparam, formerly foof⁸). Grey shading: 95% confidence-interval (CI) of population power ($N = 90$ participants from datasets I, II, and IV). Group averaged of bands detected by specparam are presented in (B), and peaks in (C). Dashed lines in (B), (C), (E), (F), and (H) at 4, 8, 12, and 30 Hz denote borders between canonical bands⁹. (D) Median rhythmicity levels are stable across participants and data types. Grey (pink) traces denote the mean and shades the 95% CI of the median of 90 subjects (pink-noise) using different lags and wavelet widths. Note that with 5 or more wavelet length, and 2 or less cycle lags, noise and data are indistinguishable. This allows using surrogate data to estimate noise floor and significance levels, as further discussed in Supplementary Text, Parametrical effects on rhythmicity measures, and fig. S6. Star denotes the values used throughout the manuscript. (E) Black: Mean $\pm$ 95% CI of the population ($N = 90$ participants) rhythmicity values. Pink: mean $\pm$ 95% CI of the medians of each participant. (F) Population summary of significantly ($p < 0.05$) sustained peaks detected by ABBA. (G) Forest plot of significant bands. Circle: peak (or trough) of each participant. Green horizontal lines: limits of rhythmic bands. Blue horizontal lines: limits of arrhythmic bands. Note that although the ranges of bands are stable and agree with canonical bands⁹, there is a considerable degree of inter-subject variability, which can lead to erroneous band-definition and deems individual band definition necessary. (H). Population ($N = 90$ participants) summary of significantly ($p < 0.05$) transient peak-frequencies (i.e., troughs in LAVI) detected by ABBA. Source data are provided as a Source Data file.



Supplementary Figure S3. Band-specific burst-statistics.

The duration (A,B), rate (C), occupancy (D), relative power (E) and band frequency consistency (F) of oscillatory bursts in EEG data (N=172 participants, blue and green distributions, corresponding to bursty and sustained bands respectively) and simulations with participant-matched aperiodic 1/f noise (pink distributions). Violin plots represent the whole distribution, horizontal lines the median. *- p<0.05, **- p<0.01, ***- p<0.001, ns- not significant, ANOVA with Tukey's post-hoc. Exact

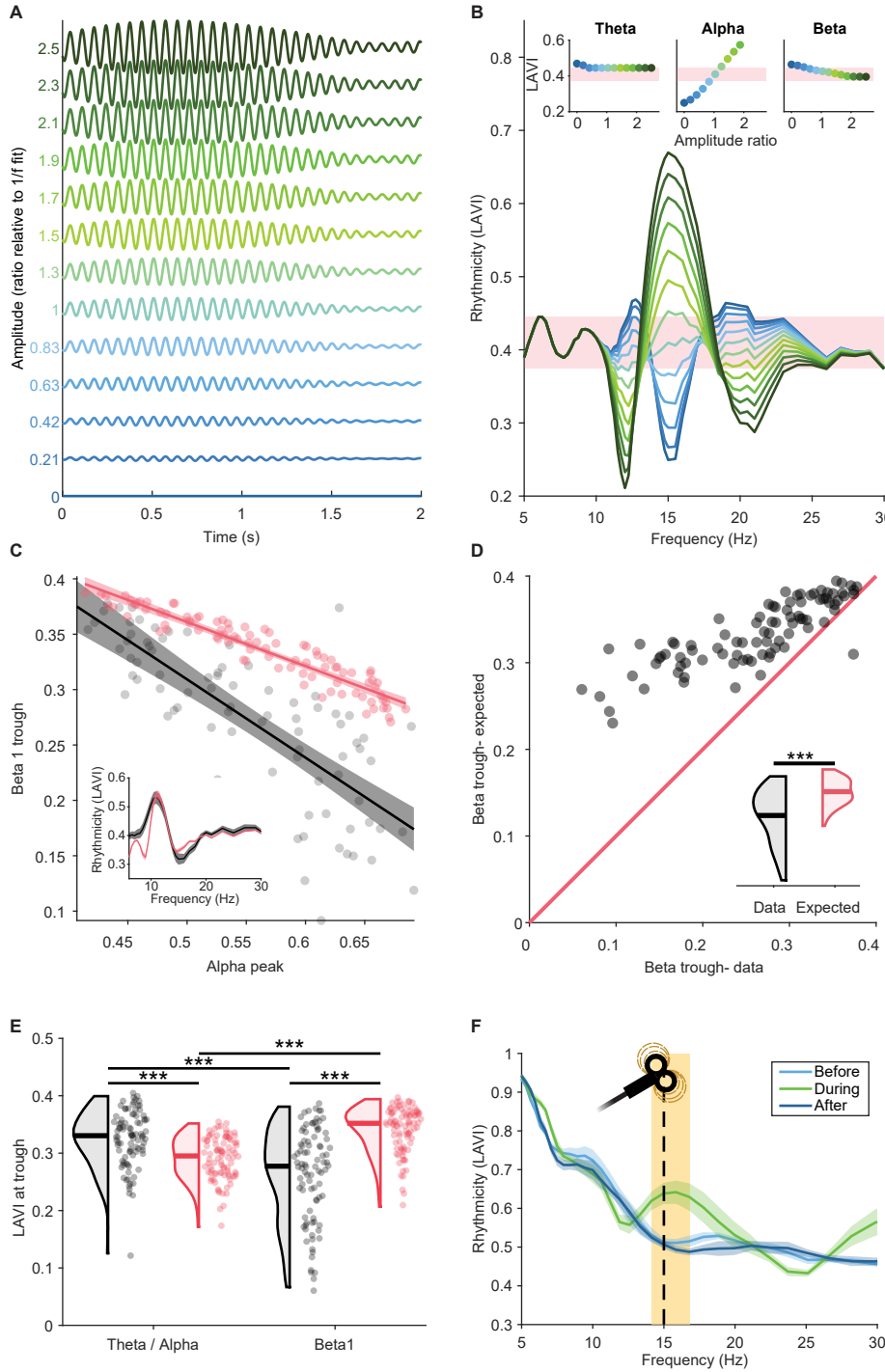
p-values are provided in the Source Data file. **(G)** Comparison of distributions of pink-noise simulations collapsed for low- and high-rhythmicity, from dataset I ($N = 37$ participants, compare to recorded data in main Fig. 3B-F). Source data are provided as a Source Data file.



Supplementary Figure S4. The effect of repeating pulses and frequency drifts on rhythmicity

A-B: Bursts with frequency drifts. Each burst consisted of 10 cycles, and the frequency drifted linearly from 15 Hz plus half the value on the y-axis to 15 Hz minus half the value. **B:** the effect on rhythmicity. Note that frequency drift reduces rhythmicity, however, rhythmicity remains above noise-level up to drifts of 5 Hz (33% of original frequency).

C-D: Rhythmic pulses, **E-F:** Arrhythmic pulses. **C, E:** Simulations design. Synchronized (**C**) or asynchronous (**E**) transient inputs were simulated as trains of strong pulses. The first and last inputs in a train were time locked to the same duration, whereas the intervals between inputs within trains were constant in **C** and randomized in **E**. **D, F:** The response of the rhythmicity profile to synchronized (**D**) or asynchronous (**F**) inputs. Colour code identical to main Fig. 3H. Note rhythmicity levels higher than expected by noise with 5 or more synchronized pulses (**D**), but no effect of number of pulses on rhythmicity with asynchronous pulses (**F**). Source data are provided as a Source Data file.



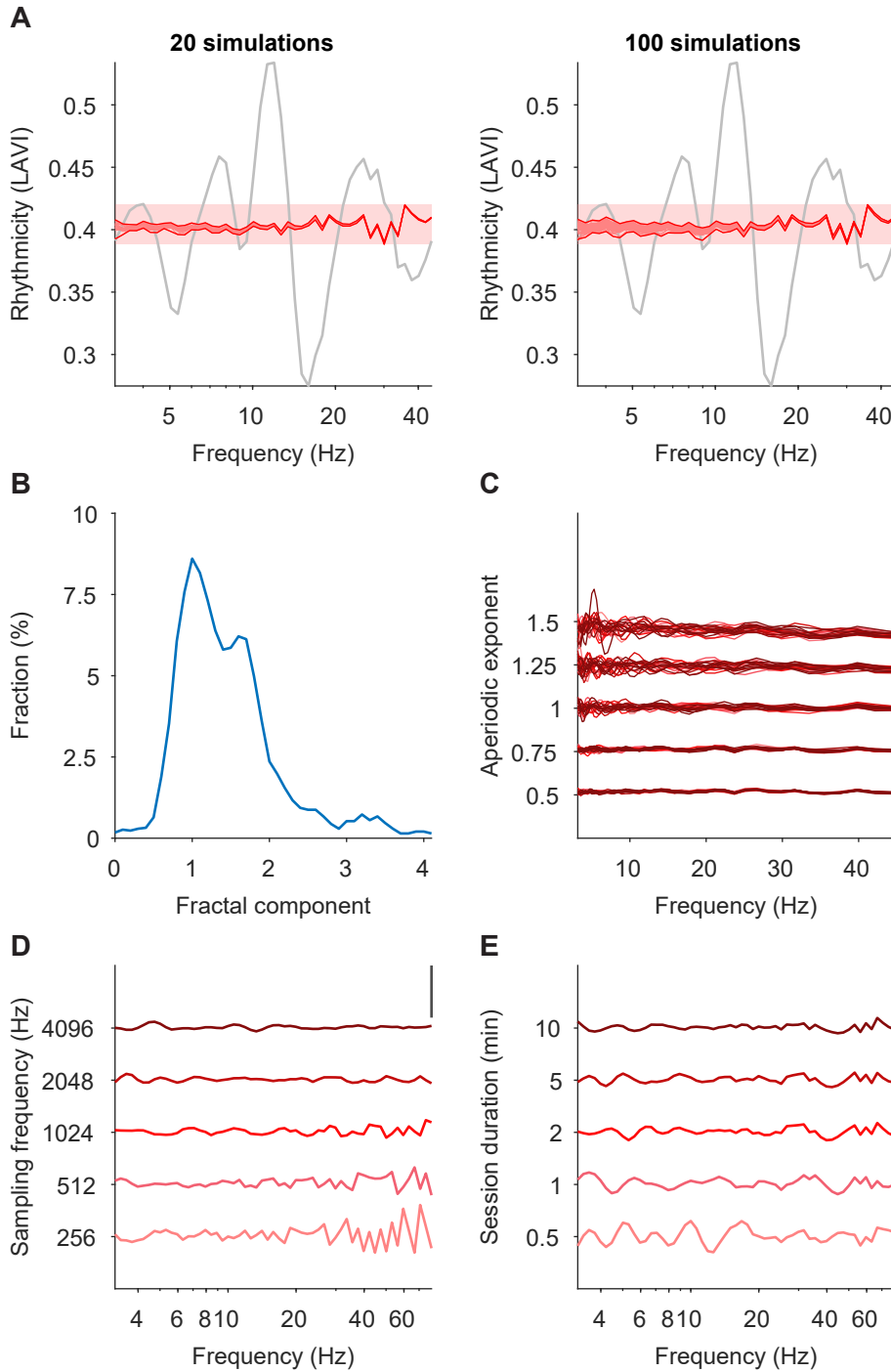
Supplementary Figure S5. Transient bands are more arrhythmic than expected by interference shadows from neighbouring rhythmic bands.

(A-B) Potential cross-frequency effects on the rhythmicity profile. Reducing the power in one frequency, e.g. by filtering (A, blue traces) reduces the rhythmicity in this frequency below expected by pink-noise (B), but also increases rhythmicity in neighbouring frequencies. Conversely, increasing the power (green traces) increases rhythmicity in the manipulated frequency and reduces rhythmicity in the neighbouring frequencies. This interference shadow can theoretically be the (artefactual) source of troughs in the rhythmicity profile that would be erroneously defined as arrhythmic bands.

(C) Rhythmicity levels (LAVI) at the alpha peak vs. the beta1 trough of 90 participants (black) or pink-noise (pink). To generate the pink noise distribution, we created 90 instantiations of 120 s pink noise, each with power at 11 Hz (alpha) randomly chosen between 1.05 to 2.25 of the original (1/f) value. Dots: individual subjects/ noise instantiations. Lines: linear regression. Shades: 95% prediction intervals. Data: Pearson = -0.832, $p < 10^{-23}$. Noise: = -0.941, $p < 10^{-42}$. Inlet: Population mean $\pm$ 95% CI of rhythmicity values. (D) Based on the alpha-to-beta1 linear regression of pink-noise, we compared the beta1 rhythmicity levels measured in the data (abscissa) to the beta1 levels expected given the alpha peak levels of each participant. Note that 89 out of

90 participants (99%) were above the unity line, indicating that their beta1 trough is lower than expected by interference shadows from alpha ($t_{89}=12.7$, $p < 10^{-20}$, inlet). (E) Beta1 trough is more arrhythmic than expected by alpha interference. For each of the 90 participants we created a 3 min surrogate pink-noise trace, with matched aperiodic component and alpha power (10 Hz) matching the original (non-fit) value, and extracted the rhythmicity levels at the trough between theta and alpha and the beta1 trough of both data (black) and surrogate (pink). Rainclouds show the full distribution. Horizontal lines: median. Two-way ANOVA (band and data type): main effect for band: $F_{1, 356}=0.98$, $p=0.32$; main effect for data type: $F_{1, 356}=15.4$, $p < 10^{-3}$; interaction: $F_{1, 356}=95$, $p < 10^{-19}$. ***- $p < 0.001$, post-hoc t-test with Bonferroni correction. The significant interaction indicates that the artefactual interference effect of rhythmic alpha is expected to be stronger on lower frequencies, but in the data the beta1 trough is more arrhythmic than expected by noise and in comparison to the theta-alpha trough. Exact p-values

are provided in the Source Data file. (F) Repetitive TMS increases rhythmicity in the stimulated frequency, but the interference shadow does not reach significance. The rhythmicity levels of $N = 6$ participants before (light blue, line denotes mean and shading $\pm$ SEM), during (green) and after (dark blue) 6 rhythmic TMS stimulations at 15 Hz (dashed line). Yellow shaded area: rhythmicity during is different than before/ after ($p < 0.05$, cluster permutation test). Source data are provided as a Source Data file.



Supplementary Figure S6. Parameters affecting pink- noise simulation.

A. The number of pink-noise simulations (pink traces) has minimal impact on the estimated noise ribbon. Two approaches are suggested for defining the noise ribbon: (1) per-frequency limits (red traces), and (2) global minimum–maximum values across the spectrum (pink shading). Grey trace shows the LAVI profile of empirical data. In this example (sampling rate = 512 Hz; simulation duration = 3 min; aperiodic exponent = 1.1), the number of simulations slightly affects low frequencies. The second (global) approach is more sensitive to high-frequency variance, but remains stable across simulation counts. Notably, low-frequency variation is primarily driven by the aperiodic exponent (panel C) and session duration (panel E), while high-frequency variability is mainly influenced by the sampling rate (panel D). **B.** Distribution of aperiodic (fractal) exponents of empirical data, with most values falling between 0.5 and 2—typical of "pink" noise. **C-E.** Effects of simulation parameters on the LAVI spectrum.

C. Varying the aperiodic exponent (noise exemplified via 20 simulations). **D.** Varying the sampling frequency. **E.** Varying the duration of the simulated session. Vertical bars in (C-E) denote LAVI = 0.1. Source data are provided as a Source Data file.

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