
Falling asleep follows a predictable bifurcation dynamic

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Supplementary Materials

Supplementary Notes

Fold (saddle-node) bifurcation

A bifurcation is a ‘qualitative’ shift of the system’s state or behaviour in response to a smooth and gradual change in the (control) parameter of a dynamical system. The type of qualitative change (bifurcation) depends on how the system’s equilibria (a.k.a. steady states where the system can remain, in our case, wakefulness or sleep states in the brain) are created or destroyed or change in their stability. The fold bifurcation is a specific type of bifurcation, where the gradual change in the control parameter causes the original stable equilibrium to disappear, or more formally, collide with another non-observable (i.e., exists theoretically) unstable equilibrium and annihilate. This will lead the system to have an abrupt discontinuous transition to another state, sometimes also described as a catastrophic regime shift. The point at which this bifurcation occurs is also known phenomenologically as the tipping point (or the point of no return). A simple, illustrative example would be bending a stick (see illustration in Fig.S1): we start with no force and gradually increase our force (control parameter) to bend it; the stick will show minor deformation until at some point, when the force is strong enough (at the tipping point), the stick will snap, which is a catastrophic change into a new system state with the original state disappeared. This is an extreme example where the transition is not reversible; in many natural systems, however, the bifurcations are reversible, and they can follow a different return path, thus leading to hysteresis¹.

Earlier experimental evidence of a falling asleep bifurcation

To our knowledge, this is the first experimental evidence that the brain's falling asleep phenomenon displays a bifurcation dynamic. Our findings address the long-lasting gap in our understanding of the falling asleep dynamic as a continuous process supporting the bifurcation concept hypothesised using neural circuit modelling. We note a recent case report (two human participants) that reported the feasibility of early warning signals (such as EEG autocorrelation and variance) shortly (~25s) before different sleep stage transitions, although not between wake and sleep². We also note a recent study that showed critical slowing down in an autoregressive integrated moving average model of heart rate variability as participants stopped responding to instructions (button press) while falling asleep (no brain activity was measured)³.

Earlier demonstration of real-time prediction of progression into sleep

To our knowledge, this is the first demonstration of real-time prediction of the brain's progression into sleep. We note the report by Prerau et al.⁴, who derived a probability of losing behavioural response while falling asleep, quantified by the accuracy of pressing a stress ball during breath inhales. The authors derived a Bayesian model summing a state process based on a muscle’s electromyography (EMG) amplitude during ball pressing and state processes based on the brain’s alpha and delta-theta band powers. The authors showed a large inter-subject heterogeneity in the behavioural loss, but improved tracking accuracy overall compared to normal sleep stages. Yet, using an active task such as ball-pressing to quantify the falling asleep process can bias the natural phenomenon⁵. In addition, the changes in behavioural response do not represent the complex changes in brain activity during falling asleep. Other reports, such as those by Strauss et al.⁶ and Jagannathan et al.⁷ linked a set of EEG features to subgroups of Hori micro-states⁸ (manually scored) and vigilance (assessed using auditory evoked potential or choice response task). The computational framework described in this paper is distinct from these earlier works. Instead of linking changes in brain activity to changes in behavioural response⁴ or Hori micro-states^{6,7} during the falling asleep process, we describe the changes in brain activity themselves. We also note the recent report by Haasan et al. that focused on changes in brain activity⁹. The authors clustered three states, i.e., wakefulness, drowsiness, and sleep during falling asleep (wakefulness and N1 stages), using a sigmoid-shaped wakefulness probability function derived from a weighted sum of normalised changes in EEG band powers (delta, alpha, and beta). Our description of the changes in brain activity goes beyond discrete states, providing a continuous measure of the sleep-relevant changes with a defined wake–sleep cutoff. In contrast to earlier

approaches, our descriptive model is entirely data-driven without an assumption on the governing features or a need for hyperparameter fiddling. Finally, we note prediction attempts using other physiological measures, such as heart rate variability³, respiratory¹⁰, and body temperature¹¹ (alas, without benchmarking to brain EEG changes or sleep staging). However, these physiological metrics do not capture the high temporal dynamics of the brain falling asleep¹². Hence, they may support brain-based measures but not replace them. This would be especially the case in patients with sleep-onset disorders such as paradoxical insomnia¹³.

Supplementary Figures

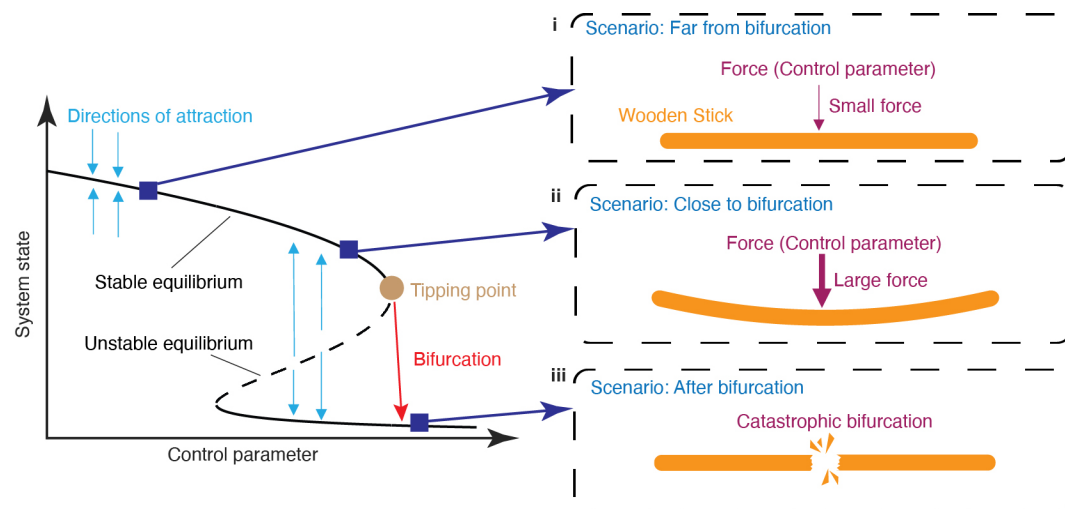


Fig.S1. Illustration of the bifurcation process via the bending stick example.

A representative fold (saddle-node) bifurcation diagram(left) and the analogy of a bifurcation process during the bending of a stick (right). In the bifurcation diagram, the solid line shows the stable equilibria, while dashed lines show unstable ones. The light blue arrows show the directions of attraction (i.e., where the system states would go if they were not at equilibrium). The tipping point (orange dot) is where the stable and unstable equilibria collide and annihilate, leading to a bifurcation into a completely different state (the bottom equilibrium).

The bending stick bifurcation process shows the changes in the system state (stick integrity) as a function of the control parameter (bending force). When the force is small, the stick shows minor or no deformation ((i), far from bifurcation). With the gradual increase of the force, the stick shows larger deformation (ii). When the force surpasses the tipping point value, bifurcation happens, and the stick would break (iii), with the original state (a complete stick) disappearing.

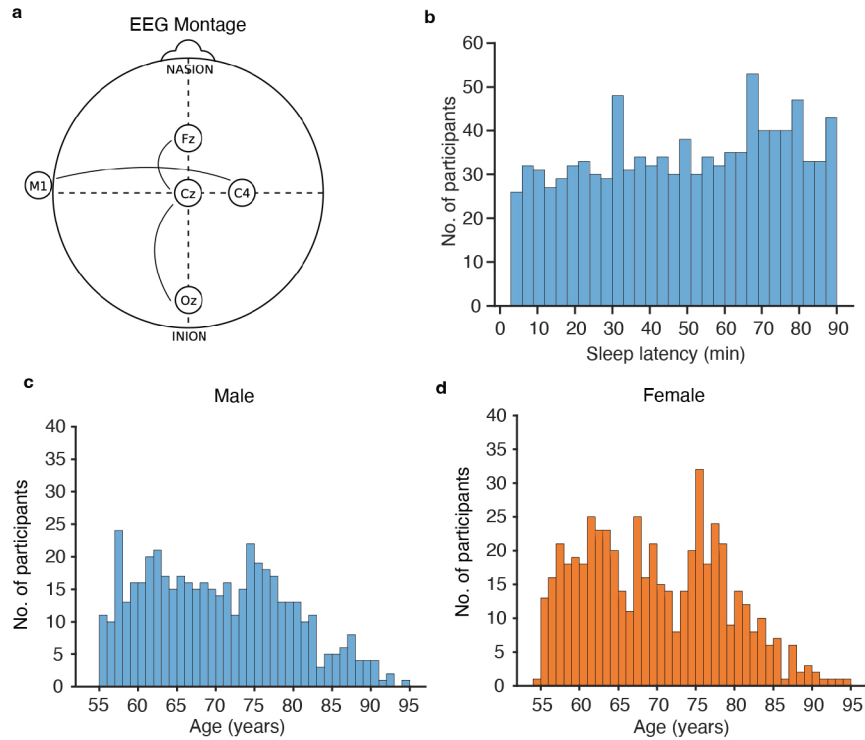


Fig.S2. Cohort 1 information (related to Fig.2-3).

Cohort 1 is from the Multi-Ethnic Study of Atherosclerosis (MESA) dataset^{14,15}.

a, Recording electrode montage, including Fz-Cz, Cz-Oz and C4-M1 derivations of the 10-20 system.

b, Distribution of participants' sleep onset latency (n = 1011).

c, Distribution of male participants' age (n = 477).

d, Distribution of female participants' age (n = 534).

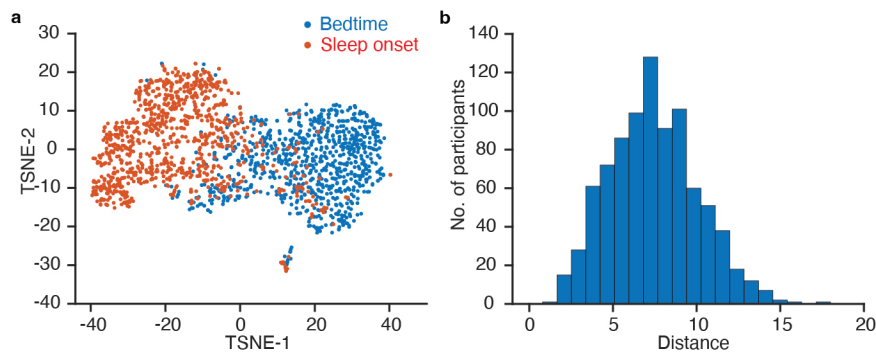


Fig.S3. The distinctiveness of bedtime and sleep onset states in the feature space (related to Fig.2).

a, Distribution of the participant's bedtime state (orange) and sleep onset state (blue) centroids, visualised in a 2-dimensional (2D) using t-distributed stochastic neighbour embedding (t-SNE).

b, Histogram of participant's Euclidean distances between bedtime and sleep-onset states in the feature space.

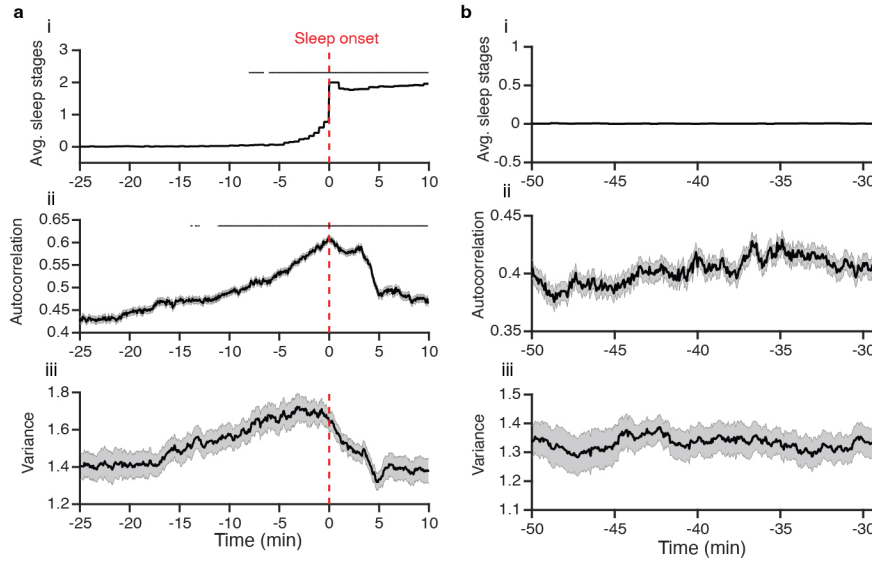


Fig.S4. Critical slowing down and early warning signals (related to Fig.2).

a. Group-averaged (i) sleep stage, (ii) autocorrelation, and (iii) variance of the participants' sleep distance $s(t)$ time series computed from 30 minutes before to 10 minutes after sleep onset. Showing mean value (black line) and standard error of the mean, s.e.m., (shaded areas). Horizontal lines at the top of the panel indicate a significant increase compared to the first 3 minutes computed using a right-tailed two-sample t-test with a p-value threshold Bonferroni corrected for the number of timestamps. Vertical red dashed line indicates sleep onset time. Linear mixed effect model: For autocorrelation, the Linear mixed effect model coefficient (with time as predictor and participant index as random effect) was 0.006, $F_{(1,2.52 \times 10^5)} = 268.84$, $p = 2.19 \times 10^{-60}$. For Variance, coefficient 0.008, $F_{(1,3.52 \times 10^5)} = 31.85$, $p = 1.69 \times 10^{-8}$ ($n = 626$).

b. Same as **a** but for a period without falling asleep transition (see Methods for details). Linear mixed effect model: For autocorrelation, the Linear mixed effect model coefficient was 0.0004, $F_{(1,2.21 \times 10^5)} = 0.87$, $p = 0.35$. For Variance, coefficient -0.0009, $F_{(1,2.07 \times 10^5)} = 0.52$, $p = 0.47$ ($n = 425$).

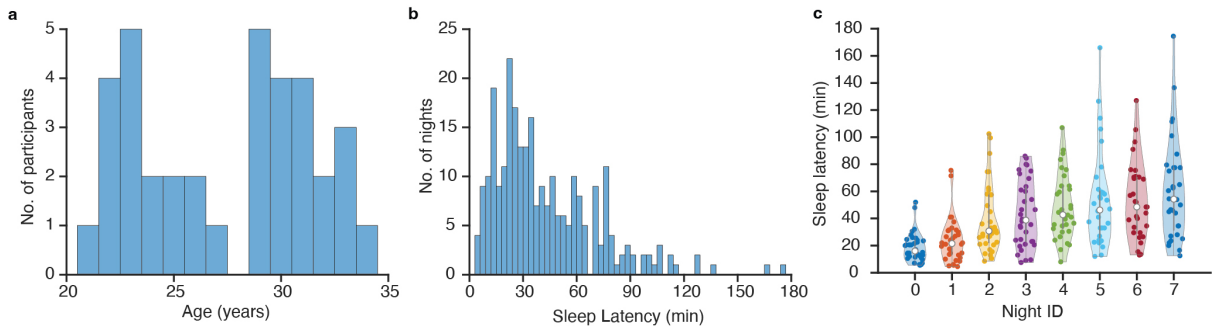


Fig.S5. Cohort 2 information (related to Fig.4).

a. Distribution of participants' age ($n = 36$).

b. Distribution of all participants' sleep latency ($n = 267$).

c. Sleep latency distribution grouped by night number (i.e., the day of the lab visit). The violins show the kernel density (the shape), the median values (white non-filled circle) and upper and lower 25% quantiles (grey bar). Refer to Table S6 for their statistics.

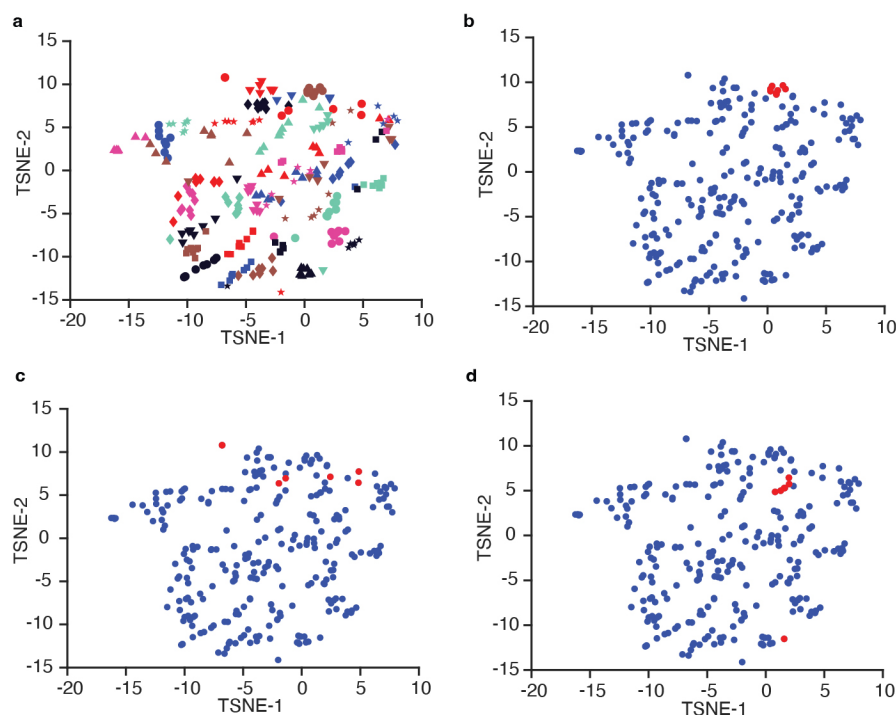


Fig.S6. Two-dimensional distribution of individual sleep onset centroids computed using t-SNE (related to Fig.4).

a, 2-D view of the participants' feature space sleep onset centroids. Each colour-marker pair denotes nights from the same participants ($n = 267$ nights for $n = 36$ participants in total). The x and y axes are t-SNE embedding dimensions.

b, Same as **a**, but with a representative participant with consistent sleep onset centroid across nights in red (tested via the Silhouette score test) and the remaining participants in blue.

c, Same as **b**, but for a participant without a consistent sleep onset centroid.

d, Same as **b**, but for a participant with most of the nights consistent, except one.

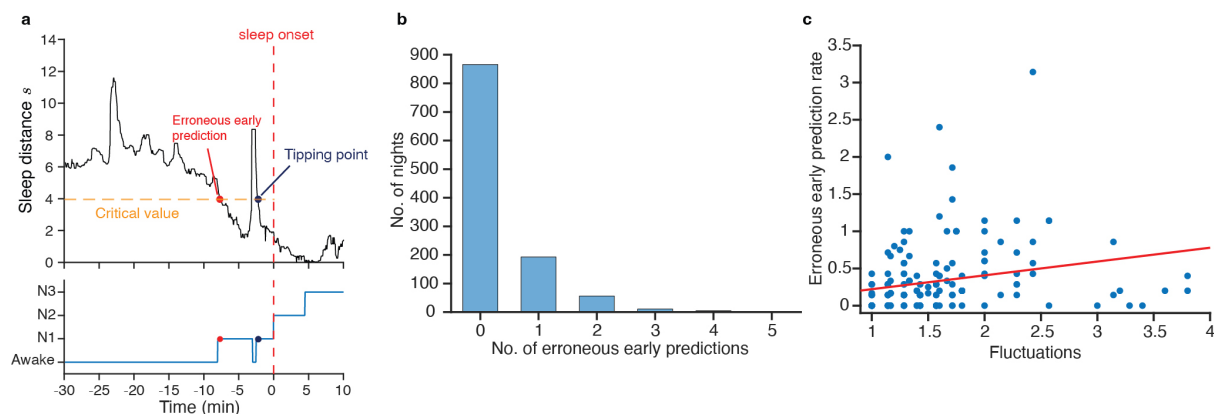


Fig.S7. Cases of erroneous early tipping point prediction (related to Fig.4).

a, An exemplary case of erroneous early tipping point prediction. The blue circular marker indicates the tipping point, and the red circular marker indicates an earlier crossing of the sleep distance critical value. The orange horizontal line shows the critical threshold determined by the training model. The red vertical dashed line shows the sleep onset. The bottom panel shows the corresponding hypnogram of that night, with the red and blue tipping point markers copied.

b, Histogram of the number of erroneous early tipping point predictions across all the testing nights (with random training night picked and repeated five times).

c, Correlation between the probability of erroneous early tipping point prediction (averaged per training case, in total $n = 180$) and the hypnogram fluctuations (i.e., number of sleep stage transitions). The red line shows the linear regression line, $r = 0.24$, $p = 0.001$, two-sided Pearson correlation test ($n = 179$).

Supplementary Tables

Table S1. List of EEG time series features used for analysis

List 1: Conventional EEG analysis features (25 in total)

<i>Feature code name</i>	<i>Descriptions</i>
Power-band features	
<i>Delta_power</i>	The mean delta band (0.5 – 4 Hz) power normalized to the entire spectrum power and log transformed
<i>Theta_power</i>	The mean theta band (4 – 8 Hz) power normalized to the entire spectrum power and log transformed
<i>Alpha_power</i>	The mean alpha band (8 – 12 Hz) power normalized to the entire spectrum power and log transformed
<i>Beta_power</i>	The mean beta band (12 – 30 Hz) power normalized to the entire spectrum power and log transformed
<i>Delta_to_theta_ratio</i>	The log-transformed band power ratio between delta and theta band
<i>Delta_to_alpha_ratio</i>	The log-transformed band power ratio between delta and alpha band
<i>Delta_to_beta_ratio</i>	The log-transformed band power ratio between delta and beta band
<i>Theta_to_alpha_ratio</i>	The log-transformed band power ratio between theta and alpha band
<i>Theta_to_beta_ratio</i>	The log-transformed band power ratio between theta and beta band
<i>Alpha_to_beta_ratio</i>	The log-transformed band power ratio between delta and alpha band
<i>Transition_power_ratio</i>	The log-transformed transition power ratio defined as the low frequency band power (delta plus theta) divided by high frequency band power (alpha plus beta)
<i>Peak_delta_band_frequency</i>	The peak frequency in the delta band (frequency bin with highest power)
<i>Peak_theta_band_frequency</i>	The peak frequency in the theta band (frequency bin with highest power)
<i>Peak_alpha_band_frequency</i>	The peak frequency in the alpha band (frequency bin with highest power)
<i>Peak_beta_band_frequency</i>	The peak frequency in the beta band (frequency bin with highest power)
Temporal coherence features	
<i>Temporal_coherence_delta_band</i>	The temporal coherence in delta band
<i>Temporal_coherence_theta_band</i>	The temporal coherence in theta band
<i>Temporal_coherence_alpha_band</i>	The temporal coherence in alpha band
<i>Temporal_coherence_beta_band</i>	The temporal coherence in beta band
Phase-amplitude coupling features	
<i>Phase_amplitude_coupling_DT</i>	The phase-amplitude coupling strength between delta band phase and theta band amplitude
<i>Phase_amplitude_coupling_DA</i>	The phase-amplitude coupling strength between delta band phase and alpha band amplitude
<i>Phase_amplitude_coupling_DB</i>	The phase-amplitude coupling strength between delta band phase and beta band amplitude
<i>Phase_amplitude_coupling_TA</i>	The phase-amplitude coupling strength between theta band phase and alpha band amplitude
<i>Phase_amplitude_coupling_TB</i>	The phase-amplitude coupling strength between theta band phase and beta band amplitude

<i>Phase_amplitude_coupling_AB</i>	The phase-amplitude coupling strength between alpha band phase and beta band amplitude
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List 2: Catch-22: canonical highly comparative time-series features (Reused from¹⁶ under [Creative Commons Attribution 4.0 International License](#)).

<i>Feature code name</i>	<i>Descriptions</i>
Distribution	
<i>DN_HistogramMode_5</i>	Mode of z-scored distribution (5-bin histogram)
<i>DN_HistogramMode_10</i>	Mode of z-scored distribution (10-bin histogram)
Simple temporal statistics	
<i>SB_BinaryStats_mean_longstretch1</i>	Longest period of consecutive values above the mean
<i>DN_OutlierInclude_p_001_mdrmd</i>	Time intervals between successive extreme events above the mean
<i>DN_OutlierInclude_n_001_mdrmd</i>	Time intervals between successive extreme events below the mean
Linear autocorrelation	
<i>CO_flecac</i>	First 1/e crossing of autocorrelation function
<i>CO_FirstMin_ac</i>	First minimum of autocorrelation function
<i>SP_Summaries_welch_rect_area_5_1</i>	Total power in lowest 1/5 of frequencies in the Fourier power spectrum
<i>SP_Summaries_welch_rect_centroid</i>	Centroid of the Fourier power spectrum
<i>FC_LocalSimple_mean3_stderr</i>	Mean error from a rolling 3-sample mean forecasting
Nonlinear autocorrelation	
<i>CO_trev_1_num</i>	Time-reversibility statistic, $\langle (x_{t+1} - x_t)^3 \rangle_t$
<i>CO_HistogramAMI_even_2_5</i>	Automutual information, $m=2, \tau=5$
<i>IN_AutoMutualInfoStats_40_gaussian_fmfi</i>	First minimum of the automutual information function
Successive differences	
<i>MD_hrv_classic_pnn40</i>	Proportion of successive differences exceeding 0.04σ
<i>SB_BinaryStats_diff_longstretch0</i>	Longest period of successive incremental decreases
<i>SB_MotifThree_quantile_hh</i>	Shannon entropy of two successive letters in equiprobable 3-letter symbolization
<i>FC_LocalSimple_mean1_tauresrat</i>	Change in correlation length after iterative differencing
<i>CO_Embed2_Dist_tau_d_expfit_meandiff</i>	Exponential fit to successive distances in 2-d embedding space
Fluctuation Analysis	
<i>SC_FluctAnal_2_dfa_50_1_2_logi_prop_r1</i>	Proportion of slower timescale fluctuations that scale with DFA (50% sampling)
<i>SC_FluctAnal_2_rsrangefit_50_1_logi_prop_r1</i>	Proportion of slower timescale fluctuations that scale with linearly rescaled range fits
Others	
<i>SB_TransitionMatrix_3ac_sumdiagcov</i>	Trace of covariance of transition matrix between symbols in 3-letter alphabet
<i>PD_PeriodicityWang_th0_01</i>	Periodicity measure of ¹⁷

List 3: Additional specific EEG characterisations related to sleep (3 features)

<i>Feature code name</i>	<i>Descriptions</i>
Power-band features	
<i>Sigma_power</i>	The mean sigma band (12-16 Hz) power normalized to the entire spectrum power and log transformed; This band is the one within which spindles happen.
<i>LZ_Complexity</i>	A normalised version of Lempel-ziv complexity (the entropy rate estimation of the EEG signal) is implemented, which estimates how many bits of innovation are introduced by each data sample, and how hard to predict the next ¹⁸ ; This has

	also been shown to be better than directly using the Lempel-ziv complexity measurement ¹⁹ .30/08/2025 22:44:00
<i>If_Slope</i>	The 1/f slope (aperiodic component) of the EEG power spectrum, estimated using the FOOOF toolbox ²⁰ at a broadband (0.1-32 Hz). The output feature values were reflected, where a larger value indicates a sharper slope (i.e., more power at low-frequency parts).

Table S2. Interpretation of the representative FPC features mentioned in the main text.

Feature code name	Name used in text	Explanations
Theta_power	Theta band power	As described in the method;
Delta to alpha ratio	Delta-to-alpha ratio	As described in the method;
Theta to beta ratio	Theta-to-beta ratio	As described in the method;
Peak theta band frequency	Peak theta frequency	As described in the method;
Peak beta band frequency	Peak beta frequency	As described in the method;
Temporal_coherence_theta_band	Theta temporal coherence	As described in the method;
Temporal_coherence_alpha_band	Alpha temporal coherence	As described in the method;
SB_BinaryStats_mean_longstretch1	Dwelling time	A catch22 feature evaluated as the longest period of time that the EEG data would be above its mean. The slower the EEG is fluctuating around its mean (e.g., slower frequency), the larger the feature value.
SP_Summaries_welch_rect_area_5_1	Total spectrum power	This feature captures the first fifth total spectrum power; Given that our EEG sampling rate is 256Hz, the first fifth of the spectrum ranges from 0 to around 25Hz; In the typical scenario of sleep EEG the spectrum power is mostly concentrated below 30Hz, so we interpret it as approximately the 'total spectrum power'.
SP_Summaries_welch_rect_centroid	Spectrum centroid	This feature measures the centroid of the EEG power spectrum, estimating where the spectrum energy is concentrated. Lower feature values imply that the energy is concentrated in lower frequency bands.
FC_LocalSimple_mean3_stderr	Prediction Error	This feature measures the error for predicting future 3 samples within the EEG signal; The larger the value, the lower predictable the EEG will be; for instance, a slow changing EEG will be very predictable (thus low feature values).
LZ_Complexity	Lempel-Ziv Complexity	As described in the method;
If_Slope	Spectral slope	As described in the method;

Table S3. The cosine similarity and DTW distances between the control parameter and the features (related to Fig.3).

The best representative feature is marked in red.

Feature code name	DTW distance	Cosine similarity	Similarity / DTW
Delta_power	66.23	0.94	0.014
Theta_power	66.22	0.88	0.013
Alpha_power	65.19	0.79	0.012
Beta_power	42.72	0.52	0.012
Delta to theta ratio	31.32	0.13	0.004
Delta to alpha ratio	49.07	0.76	0.016
Delta to beta ratio	66.03	0.96	0.014
Theta to alpha ratio	63.26	0.97	0.015
Theta to beta ratio	66.33	0.90	0.014
Alpha to beta ratio	65.53	0.81	0.012
Transition power ratio	65.66	0.96	0.015
Peak delta band frequency	66.07	0.88	0.013
Peak theta band frequency	11.31	0.82	0.073
Peak alpha band frequency	39.85	0.43	0.011

Peak beta band frequency	13.28	0.88	0.066
Temporal coherence delta band	31.88	0.13	0.004
Temporal coherence theta band	6.69	0.94	0.140
Temporal coherence alpha band	7.10	0.93	0.132
Temporal coherence beta band	14.53	0.74	0.051
Phase amplitude coupling DT	13.50	0.83	0.061
Phase amplitude coupling DA	14.73	0.80	0.054
Phase amplitude coupling DB	17.05	0.78	0.046
Phase amplitude coupling TA	15.77	0.75	0.048
Phase amplitude coupling TB	19.01	0.68	0.036
Phase amplitude coupling AB	28.53	0.25	0.009
DN HistogramMode 5	33.11	0.16	0.005
DN HistogramMode 10	30.51	0.14	0.005
CO flecac	65.69	0.82	0.013
CO FirstMin ac	65.24	0.80	0.012
CO HistogramAMI even 2 5	16.71	0.72	0.043
CO trev 1 num	27.92	0.23	0.008
MD hrv classic pnn40	14.93	0.82	0.055
SB BinaryStats mean longstretch1	66.08	0.86	0.013
SB TransitionMatrix 3ac sumdiagcov	14.69	0.81	0.055
PD PeriodicityWang th0 01	64.91	0.78	0.012
CO Embed2 Dist tau d expfit meandiff	65.40	0.80	0.012
IN AutoMutualInfoStats 40 gaussian fnmi	21.55	0.70	0.032
FC LocalSimple mean1 tauresrat	16.95	0.83	0.049
DN OutlierInclude p 001 mdrmd	29.87	0.20	0.007
DN OutlierInclude n 001 mdrmd	30.52	0.17	0.006
SP Summaries welch rect area 5 1	65.63	0.82	0.012
SB BinaryStats diff longstretch0	65.14	0.79	0.012
SB MotifThree quantile hh	17.47	0.81	0.047
SC FluctAnal 2 rsrangeft 50 1 logi prop r1	65.91	0.89	0.014
SC FluctAnal 2 dfa 50 1 2 logi prop r1	33.42	0.12	0.004
SP Summaries welch rect centroid	17.78	0.81	0.046
FC LocalSimple mean3 stderr	15.54	0.84	0.054
Sigma power	66.04	0.85	0.013
LZ Complexity	13.97	0.86	0.062
lf Slope	66.42	0.91	0.014

Table S4. The mean Silhouette scores and number of participants with consistent sleep onset centroids with only one feature instead of the feature space (related to Fig.4)

Feature code name	Silhouette scores (mean $\pm$ std across all participants)	No. participants with consistent centroids (p<0.05) out of 36 participants
Theta_power	-0.42 $\pm$ 0.32	2 (5.5%)
Delta_to_alpha_ratio	-0.38 $\pm$ 0.28	0 (0%)
Peak_beta_band_frequency	-0.42 $\pm$ 0.32	1 (2.7%)
SB_BinaryStats_mean_longstretch1	-0.48 $\pm$ 0.34	3 (8.3%)
SP_Summaries_welch_rect_area_5_1	-0.47 $\pm$ 0.26	0 (0%)
SP_Summaries_welch_rect_centroid	-0.46 $\pm$ 0.33	2 (5.5%)
FC_LocalSimple_mean3_stderr	-0.45 $\pm$ 0.30	2 (5.5%)

Table S5. Statistics of cosine similarity for different numbers of training nights used (related to Fig.4bii)

No. of training nights	Cosine similarity (mean $\pm$ st.d.)
1	0.95 $\pm$ 0.06
2	0.97 $\pm$ 0.03
3	0.97 $\pm$ 0.03
4	0.97 $\pm$ 0.03
5	0.97 $\pm$ 0.04
6	0.98 $\pm$ 0.02
7	0.98 $\pm$ 0.03

Table S6. Sleep latency statistics per night visit for the second cohort (related to Fig.S5)

Night ID	Mean latency (min)	St.d.
1	18.81	10.78
2	23.93	16.26
3	39.49	24.69
4	43.31	24.54
5	48.53	23.39
6	53.25	35.62
7	53.11	28.00
8	60.83	37.09

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