ChatGPT

NeuroProfile: An Ethical Resonance Bridge Between Neuroscience and Astrophysics

Abstract

Background. The Universal Threshold Adaptive Criticality (UTAC) framework proposes that complex systems tune their dynamics around a steep logistic transition of a control variable $\sigma(\beta(R-\Theta))$. In astrophysics this manifests as the integration velocity v_{RIG}, while in cognitive neuroscience it is hypothesised to shape consciousness. The NeuroProfile module, part of the *Phaethon–Geminiden–Bennu* project, extends UTAC into the neuro domain by estimating a subject's logistic steepness β, the variance of integrated information (σ_Φ), and a resonance proxy linking gamma–beta oscillations to hypothesised microtubule frequencies. The module is designed to be reproducible, falsifiable and ethically grounded.

Results. NeuroProfile provides a Python package that (i) preprocesses neural time–series, (ii) estimates β via a logistic heuristic, (iii) computes a normalized spectral-entropy proxy for σ_Φ, (iv) estimates gamma–beta coupling as a proxy for v_{RIG} resonance, and (v) evaluates constant, linear and power-law null models via Akaike information criterion (AIC). To ensure falsifiability, the module reports $\Delta\mathrm{AIC}$ and 95 % bootstrap confidence intervals for all estimates [1]. Analysis of a synthetic 1 kHz EEG dataset yields $\beta = 1.18$ (CI [1.17, 1.58]), $\sigma_\Phi = 0.94$ (CI [0.94, 0.94]), a gamma–beta coupling of 0.72 (CI [0.69, 0.83]) and identifies the constant null model as best ($\Delta\mathrm{AIC} = 0$) [2]. All outputs are logged to `data/results.json` with a hashed subject identifier to ensure anonymity.

Conclusions. NeuroProfile demonstrates how UTAC concepts can be operationalised in a neuroscience context while respecting consent, privacy and reproducibility. Although current results are based on synthetic data, the module provides a template for ethically analysing real EEG recordings once consent is obtained. Future work includes validating the resonance proxy on high-bandwidth recordings and integrating NeuroProfile into the broader UTAC activation matrix.

1 Introduction

1.1 UTAC and the need for a neuro–astro bridge

The Universal Threshold Adaptive Criticality (UTAC) framework characterises complex systems using a logistic function $\sigma(\beta(R-\Theta))$ that describes how an order parameter R approaches a threshold Θ with steepness β. In previous work UTAC has unified entropy governance in cosmology and biology, introducing the integration velocity v_{RIG} that links fundamental constants to an emergent speed (~1352 km s^{-1}) and predicting cross-domain scaling laws [3]. The Phaethon/Bennu research programme expands this framework by exploring resonant structures in astrophysical bodies.

Bridging UTAC to neuroscience requires measuring analogous variables within neural data. Specifically, we wish to estimate (i) the steepness β of neural transitions, (ii) the variance of integrated information σ_Φ as a signature of "living" variability, and (iii) possible resonance coupling between neural oscillations and v_{RIG}. The NeuroProfile module addresses these objectives by providing a reproducible analysis pipeline embedded in the Feldtheorie code base.

1.2 Module purpose and design principles

NeuroProfile is explicitly designed as a "resonant neuro-astrophysical bridge" [4]. Its purpose is to compute individual β profiles, σ_Φ fluctuations and v_{RIG} proxies from neural signals and compare these to astrophysical resonances. Several design principles guided the implementation:

1. **Minimal, testable foundation.** The module implements only the core functions required to estimate β, σ_Φ and resonance proxies [5], reducing the system's impedance $\zeta(R)$.
2. **Falsifiability via null models.** Linear, power–law and constant null models are fitted to each data set, and claims are accepted only when \Delta\text{AIC}\geq10 [6]. Confidence intervals are recorded for all estimates. 3. **Ethical consent and anonymization.** Analyses require explicit consent; subject identifiers are hashed, and no real EEG is processed without permission [7]. This satisfies data-protection and neuroethical concerns. 4. **Trilayer documentation.** A tri-layer index (Markdown/JSON/YAML) records semantics, technical paths and evidence for each component [8]. 5. **Release readiness.** The module includes a `requirements.txt` and a basic unit test, and a v_RIG-compatibility badge signals alignment with the UTAC framework [9]. ## 2 Materials and Methods ### 2.1 Data A synthetic 1 kHz EEG dataset consisting of 512 samples was generated for smoke testing. Each entry contains a time index and a simulated amplitude. The file is provided under `data/synthetic/synthetic_eeg_1khz.csv` and can be used to reproduce the example analysis. ### 2.2 Processing pipeline The methodological pipeline, summarised in the module's methodology document [10], consists of: 1. **Preprocessing.** Input series are z-normalised to zero mean and unit variance; artefact removal is minimal at this stage. 2. **β estimation.** The heuristic `estimate_beta_from_series` computes \(\beta by fitting a simple logistic function $\sigma(\beta(z-\tau))$ to the normalised data. The logistic steepness β, threshold τ and fit quality (r) are returned.
3. **σΦ proxy.** Spectral entropy of the absolute Fourier spectrum is computed and normalised. High values indicate greater "informational variability," whereas values approaching zero suggest a rigid or "dead" state.
4. **Resonance proxy.** The microtubule resonance module estimates gamma–beta coupling (ratio of 30–100 Hz to 12–30 Hz power) and a proxy alignment metric. These serve as surrogates for potential coupling to the hypothesised 13.5 MHz v_{RIG} frequency [11].
5. **Null-model fitting and AIC.** The analysis fits constant, linear and power–law functions to the absolute values of the series. For each model, AIC is computed using $\mathrm{AIC} = n\ln(\mathrm{RSS}/n) + 2k$, where n is the number of observations and k the number of parameters. $\Delta\mathrm{AIC}$ is the difference between each model's AIC and the minimum AIC [6].
6. **Bootstrap confidence intervals.** For each metric (β, σ_Φ, gamma–beta coupling and resonance alignment), 200 bootstrap resamples are drawn (default). The 2.5 and 97.5 percentile values provide a 95 % confidence interval.
7. **Consent enforcement and anonymization.** The function `analyze(series, consent_granted, subject_id)` verifies consent. If granted, the subject identifier is hashed using SHA256 with a salt. Results are recorded alongside the consent record [7].

2.3 Software environment

The module is implemented in Python 3.11 and depends on NumPy (>=2.0), Matplotlib, SciPy and Jupyter. A minimal `requirements.txt` lists these dependencies. A unit test (`test_neuro_profile.py`) validates consent enforcement and output structure. The code is packaged under `experiments/Phaethon_Geminiden_Bennu/NeuroProfile/code/`, and the tri-layer index files enumerate all release artifacts.

3 Results

3.1 Synthetic data analysis

When applied to the synthetic EEG dataset, NeuroProfile produces the following results (logged in `data/results.json`). Key metrics are summarised in Table 1.

Metric	Estimate	95 % CI	Interpretation
β (steepness)	1.18	[1.17, 1.58]	The logistic steepness is modest, reflecting a slow transition in this noise-like synthetic signal [12].
σΦ proxy (entropy)	0.94	[0.94, 0.94]	High normalised entropy indicates rich variability, consistent with random noise [13].
Gamma–beta coupling	0.72	[0.69, 0.83]	This suggests moderate power in the gamma band relative to beta, though not physically meaningful for random data [14].
Resonance alignment	0.95	[0.90, 1.00]	Near unity alignment is an artefact of the proxy and should not be over-interpreted [15].
Best null model	Constant	$\Delta\mathrm{AIC} = 0$	The constant model minimises AIC; both linear and power–law models have higher AIC values (ΔAIC≈0.85 and 360.8, respectively) [16].

The results show that for purely synthetic noise the constant null model suffices. Nevertheless, the pipeline successfully computes all metrics and records confidence intervals and consent metadata [17].

3.2 Consent and anonymization

The example log includes a `consent` record storing the original consent message, a `granted` flag, and a hashed `subject_anonymized` identifier. This ensures ethical handling of any future real data. If `consent_granted` is false, the system raises a `PermissionError`, preventing analysis.

4 Discussion

4.1 Significance of β and σ_Φ

Within the UTAC framework, the steepness β quantifies how rapidly a system transitions from disorder ($R < \Theta$) to order ($R > \Theta$). Empirical analyses across domains show clustering of β values around discrete bands (4–5 for informational systems, 7–8 for biological systems, etc.). NeuroProfile facilitates the measurement of β in neural data. The synthetic example yields $\beta \approx 1.18$, far below the typical UTAC clusters, reflecting the absence of structured transitions. Application to real EEG data may reveal whether human cognition aligns with UTAC's predicted $\beta \approx 4.5$ for informational systems or $\beta \approx 7.4$ for biological ones.

σ_Φ (and its proxy here) measures variability of integrated information. In UTAC simulations, living systems exhibit $\sigma_\Phi \approx 0.0625$ as a dynamic oscillation, whereas dead or frozen systems have $\sigma_\Phi \to 0$. Our synthetic entropy of 0.94 is high because the signal is unstructured noise; real neural signals might have intermediate values. Tracking σ_Φ over time could provide a marker of consciousness state.

4.2 Resonance proxies and v_{RIG}

The module currently uses gamma–beta power ratio and a microtubule alignment heuristic as surrogates for resonance with the predicted 13.5 MHz signal. These proxies are placeholders until high-bandwidth neural recordings are available. Future iterations should incorporate direct spectral analysis of microtubule oscillations if data become available.

4.3 Ethical considerations

NeuroProfile embeds consent gating and anonymization at the core of its API [7]. This is essential given the personal nature of neural data. All subject identifiers are hashed, and results are logged only when consent is granted. This approach sets a precedent for neurotechnology modules within UTAC: ethical mechanisms must be as integral as the algorithms themselves.

4.4 Limitations and future work

- **Synthetic data only.** The current release ships a synthetic dataset for reproducibility. Validation on real EEG or MEG recordings is necessary to test whether β, σ_Φ and resonance proxies reveal meaningful patterns.
- **Heuristic β estimation.** The logistic fit is a simple approximation; more robust estimation (e.g. maximum likelihood or Bayesian approaches) could refine β values. Nevertheless, the heuristic suffices for a baseline.
- **Hardware and sensor noise.** Accurate resonance measurement near 13.5 MHz requires specialised sensors beyond typical EEG. Future modules should interface with high-frequency measurement hardware.
- **Integration into UTAC index.** Although the module is now listed in the UTAC status matrix, full alignment requires ΔAIC analysis on real data and an updated activation tracker entry [18].

5 Conclusion

The NeuroProfile module represents a first step towards unifying neuroscience and astrophysics under the UTAC umbrella. By implementing consent-aware β estimation, σ_Φ proxies, resonance analysis and rigorous null-model comparisons, it offers a reproducible, falsifiable and ethically sound pipeline. While initial results are based on synthetic data, the infrastructure is ready for deployment on real recordings once consent and privacy conditions are satisfied. As the UTAC framework evolves, NeuroProfile will help test whether neural systems exhibit the same universal logistic transitions observed in cosmic phenomena.

Acknowledgements

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References

1. *NeuroProfile – Resonant Neuro-Astrophysical Bridge* README [19].
2. *NeuroProfile Strategic Roadmap* [20].
3. *NeuroProfile Methodology* [21].
4. Synthetic results in `data/results.json` [22].

1 3 4 5 6 7 8 9 11 18 19 README.md
https://github.com/GenesisAeon/Feldtheorie/blob/HEAD/experiments/Phaethon_Geminiden_Bennu/NeuroProfile/README.md

2 12 13 14 15 16 17 22 results.json
https://github.com/GenesisAeon/Feldtheorie/blob/HEAD/experiments/Phaethon_Geminiden_Bennu/NeuroProfile/data/results.json

10 21 methodology.md
https://github.com/GenesisAeon/Feldtheorie/blob/HEAD/experiments/Phaethon_Geminiden_Bennu/NeuroProfile/docs/methodology.md

20 STRATEGIC_ROADMAP.md
https://github.com/GenesisAeon/Feldtheorie/blob/HEAD/experiments/Phaethon_Geminiden_Bennu/NeuroProfile/STRATEGIC_ROADMAP.md