Entropy Coupled Trait ODEs (ECTO) Reveal Structured Population Dynamics in Longitudinal Psychometric Data

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Abstract

This project introduces ECTO, a minimal and interpretable dynamical system for modeling cohort-level trait evolution using population-level information structure. Leveraging data from the Swedish Adoption/Twin Study on Aging (SATSA), we compute a normalized entropy index $H^*(t)$ from psychometric item responses to summarize cross-sectional heterogeneity at each wave. This entropy index sets the initial condition of the system; ODEs then evolve autonomously to predict cohort dynamics, which are compared to observed data. Neuroticism, here, refers to a broad psychometric trait capturing an individual's tendency toward negative affect, including anxiety, sadness, irritability, and emotional instability, which are quantified via composite item scores (Likert scale) rather than direct biological measures. The coupled ODEs describe neuroticism ($N(t)$), its pleiotropic companion ($P(t)$), and a latent environmental stress state ($\mathrm{Estress}(t)$). ODE terms are phenomenologically inspired, encoding cohort-level analogues of mutation-selection balance, pleiotropy, metabolic constraints, and environmental feedback, but are not intended as direct biological mechanisms. ECTO's forward simulations accurately capture cohort trends and outperform an uncoupled baseline model. Out-of-sample and surrogate validations are planned to further assess robustness. ECTO is transparent, low-parameter, and fully reproducible, with preprocessing and simulation code openly available. While entropy is treated here as a summary index rather than as causal, ECTO may be applicable to other systems requiring compact representation of population heterogeneity, though extension to machine learning or agent-based contexts remains open. Current limitations include sample size and latent environment. ECTO offers a scalable template for entropy-based modeling of psychological and population-level dynamics.

Submission type: **Late Breaking Abstract**

Data/Code available at: https://anonymous.4open.science/r/ECTO_system_walkthrough-A12A/README.md

Introduction

Neuroticism is a broad psychometric construct which can be regarded as a composite tendency toward negative affect (anxiety, sadness, irritability, emotional instability)(1; 2). While the cumulative effects of negative affect can be destabilizing for individuals scoring high in neuroticism, the trait itself is remarkably stable across the life trajectory despite changing environments(3). This project asks whether information structure in population-level data recording Likert scale psychometric item responses over time can serve as a compact organizing signal to explain cohort-level trait dynamics.

Contribution

This project introduces *ECTO* (Entropy-Coupled Trait ODEs)(4): a minimal, interpretable dynamical system in which a cohort-level entropy index $H^*(t)$, computed directly from neuroticism item distributions, is used to initialize an autonomous coupled ODE for the rescaled neuroticism state $N(t)$ (with pleiotropic companion $P(t)$, where applicable). Unlike black-box models, ECTO is transparent, low-parameter, and testable(5; 6).

Data and Measure

Dataset SATSA(7), six waves (1984-2007). Flagship pair for illustration: **P8 Hot-Temperedness** (N) and **P4 Worry** (P). Note: Letter-Number prefixes refer to internal SATSA labeling retained for reproducibility.

Entropy Use Population-level entropy(8) is computed for each item within the cohort at each wave. For item j with K_j categories and counts $x_{jk}(t)$, let $p_{jk}(t) = x_{jk}(t)/\sum_m x_{jm}(t)$ and $H_j(t) = -\sum_{k=1}^{K_j} p_{jk}(t)\log_2 p_{jk}(t)$. Normalize per item and pool: $H^*(t) = \frac{1}{J}\sum_{j=1}^{J}\frac{H_j(t)}{\log_2 K_j} \in [0,1]$. H^* summarizes cross-sectional heterogeneity (not individual dispersion).

What H^* Is (and Is Not) $H^*(t)$ is a macroscopic, order-parameter-like summary of the cross-sectional response distribution at wave t(9). It is distinct from the latent states $(N, P, E_{\text{stress}})$ and is not assumed to equal or directly measure them.

Role of H^* In this work, H^* is used only to set the initial state at the first wave; the ODEs then evolve autonomously without time-varying inputs.

Model: ECTO (Coupled ODEs)

Time & Units We integrate in calendar time (years) at the observed timestamps. States and H^* are dimensionless; μ, γ have units $1/\text{year}$; $\alpha, \beta, c_1, c_2, c_3, G, K$ are dimensionless.

$$\frac{dN}{dt} = \mu N - (\alpha N + \beta^2 P)N,$$
$$\frac{dP}{dt} = \mu P - \beta P\left(\frac{c_1 P + c_2 N + c_3 E_{\text{stress}}}{G}\right),$$
$$\frac{dE_{\text{stress}}}{dt} = \gamma E_{\text{stress}}\left(\frac{N}{N+K}\right).$$

Parameters: μ ('innovation'/influx), α (self-limiting constraint), β (cross-trait coupling), γ (stress amplification), c_1, c_2, c_3 (cost weights), G (capacity; G=1 for main runs), K (saturation).

Interpretation Labels such as "mutation–selection," "pleiotropy," "metabolic constraint," and "environmental feedback" are biologically-inspired(6; 10; 11; 12; 13) phenomenological analogues at the cohort level, not direct biochemical mechanisms.

Environment Definition and Note on Lag E_{stress} is a latent cohort-level state representing external pressures (e.g., stressors, media salience, macro shocks). In this submission a measured environmental time series is not invoked; E_{stress} evolves endogenously via the equation above. The feedback loop is closed: N drives E_{stress}, which increases the metabolic cost on P, and P suppresses N via cross-trait coupling. When a measured proxy is introduced (sensitivity/poster), a one-wave lag will be utilized to keep forecasts causal under irregular gaps: on $(t_k, t_{k+1}]$ the proxy is held at its last value $Z(t_k)$ and enters only as an additive term in the stress dynamics,

$$\frac{dE_{\text{stress}}}{dt} = \gamma\, E_{\text{stress}} \frac{N}{N+K} + \lambda\, Z(t_k), \quad t \in (t_k, t_{k+1}],$$

with no contemporaneous terms.

Results to Date

- **Forward simulations** anchored at the first wave (H^* used only for initialization) reproduce broad within-sample trends for the flagship pair under plausible parameters.
- **Fit statistics** across six waves (RMSE, R^2) reported; trajectories compared to an uncoupled null with no cross-trait term.
- **Units and Scale** H^* is dimensionless on $[0, 1]$. Time is measured in years. Entropy is computed at the population level.
- **Reproducibility** Repository includes the ICPSR-to-entropy preprocessing script, simulation notebooks, and a requirements file.

Minimal Planned Additions

Roll-forward forecast from the first wave, leave-one-interval-out propagation, baselines (persistence, linear interpolation, AR(1), uncoupled 1D), plus multistart/profile-likelihood summaries and surrogate tests for any scheduled variant. This work updates the ECTO model from Rodriguez (2025) with tempered claims and expanded validation.

Applicability

$H^*(t)$ is defined for any finite categorical distribution, so it can summarize cohort-level heterogeneity in settings like survey responses, discrete behavioral choices, or community composition (e.g., species counts). Here, it is used only to set initial conditions for the ECTO ODE; no additional state variables are introduced.

Limitations

Six waves limit identifiability and preclude formal bifurcation analysis, which is desired for future iterations. E_{stress} is latent. Entropy is treated as an organizing signal rather than a proven cause.

Conclusion

While the model as currently presented is early-stage and limited in empirical scope, it provides a testable framework grounded in established biological and physical principles, and meets the goal of establishing a viable minimal formalism for future interdisciplinary development. This project ultimately aims to open new directions for interdisciplinary research.

Although this first-generation model is intentionally minimalistic, it demonstrates the feasibility of bridging entropy-based behavioral data with biologically plausible dynamic systems. Future iterations will continue to build toward a generalizable theory of trait evolution integrating environment, energy, and cognition.

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