

Cognitive Physics: A Control-Theoretic Framework for Multi-Scale Stability

Mechanisms, Operators, Estimators, and Falsifiable Predictions

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Abstract

We specify *Cognitive Physics* as a testable control-theoretic model class for adaptive stability under disturbance. The core hypothesis is a balance law linking internal structure (Coherence, C) to environmental surprise (Novelty, H), with additional mechanisms for multi-scale propagation, complexity-dependent feedback gain, a proposed spectral fixed-point claim, and an inference-time regulation law for autoregressive systems. Unlike narrative frameworks, the present document fixes (i) admissible system classes, (ii) operational estimators for each latent quantity, (iii) identifiability requirements, and (iv) predictions stated as statistical inequalities. All claims are hypotheses pending experimental validation; failure modes and rejection criteria are explicit.

1 Scope, scientific status, and rejection criteria

This document is a *model specification*. A mechanism is considered *scientifically admissible* here only if it satisfies:

1. **Operationality:** each symbol corresponds to a measurable estimator under a stated protocol;
2. **Identifiability:** the estimator is not trivially reparameterizable to force agreement;
3. **Falsifiability:** the mechanism yields predictions that can be violated by data;
4. **Domain discipline:** analogies (e.g., “spin”) are treated as indices unless a physical symmetry group and coupling are specified.

If any mechanism fails these conditions, it is *rejected or revised* rather than defended by interpretation.

2 System class and notation

We model an adaptive system with internal state $x_t \in \mathbb{R}^n$ and observations $y_t \in \mathbb{R}^m$ evolving in discrete time:

$$x_{t+1} = f(x_t, u_t, w_t), \quad y_t = h(x_t, v_t), \quad (1)$$

where u_t is an internal update/control action, and w_t, v_t are process/measurement noise. Let $\mathcal{D}_t := \{y_1, \dots, y_t\}$ denote observed data up to time t , and let \hat{y}_t denote a one-step prediction formed from \mathcal{D}_{t-1} by a specified predictor.

2.1 Estimator-first discipline

Quantities C_t , H_t , and $L64_t$ are *defined by estimators*. The theory is evaluated on the estimators, not on informal meanings.

Definition 1 (Novelty H_t (innovation energy)). Fix a predictor $\hat{y}_t = \hat{y}(\mathcal{D}_{t-1})$. Define the innovation $\nu_t := y_t - \hat{y}_t$. A canonical novelty estimator is

$$H_t := \|\nu_t\|_2^2. \quad (2)$$

Alternative admissible definitions (e.g., negative log-likelihood) must be stated explicitly and used consistently.

Definition 2 (Coherence C_t (structural capacity proxy)). Fix a representation $\phi_t := \phi(x_t)$ and a window length $W \geq 1$. Define coherence as a nonnegative estimator that increases with compressible structure or reconstructability over the window. One admissible family is

$$C_t := \mathcal{C}(\phi_{t-W+1:t}), \quad C_t \geq 0, \quad (3)$$

where $\mathcal{C}(\cdot)$ must be specified (e.g., description length, observability proxy, or predictive sufficiency score).

Definition 3 (Complexity index $L64_t$). Fix a window length of 64 steps. Define

$$L64_t := \mathcal{L}(\phi_{t-63:t}), \quad (4)$$

where $\mathcal{L}(\cdot)$ is a chosen complexity estimator (e.g., Lempel–Ziv, multiband entropy, or multiscale description length). The choice of \mathcal{L} is part of the model and must be reported.

3 Mechanism I: Balancing constraint $C - H = 0$ (closed-loop tracking)

3.1 Statement as a control objective

The balance law is treated as a *tracking objective* rather than an identity. Define the imbalance

$$e_t := C_t - H_t. \quad (5)$$

The Mechanism I hypothesis is that adaptive stability corresponds to maintaining e_t near zero under disturbance, using an internal update signal u_t .

3.2 Minimal regulated-resource model

To make the claim testable, we introduce a minimal accounting model for the coherence estimator:

$$C_{t+1} = C_t + u_t - d_t, \quad (6)$$

where $u_t \geq 0$ is the “informational work” invested at time t , and $d_t \geq 0$ is a decay/forgetting term. Both u_t and d_t must be operationalized in any empirical implementation (e.g., update magnitude, compute budget, parameter drift, or regularized code-length change).

Novelty H_t is treated as an exogenous disturbance sequence induced by the environment and the predictor class (Definition 1).

3.3 Admissible policies and feasibility

A policy is any causal map

$$u_t = \pi(\mathcal{D}_t, \phi_{t-W+1:t})$$

that respects constraints

$$0 \leq u_t \leq u_{\max}, \quad 0 \leq d_t \leq d_{\max}. \quad (7)$$

Because H_t can be arbitrarily large, exact tracking $e_t \equiv 0$ is generally *not* feasible under bounded actuation. Therefore the rigorous claim is *bounded tracking*.

3.4 Rigorous hypothesis (bounded tracking under bounded novelty)

Proposition 1 (Bounded imbalance under bounded novelty). *Assume:*

1. *the coherence accounting model (6) holds for the chosen estimator C_t ;*
2. *actuation and decay are bounded as in (7);*
3. *novelty is bounded in the operating regime: $0 \leq H_t \leq H_{\max}$ for all t ;*
4. *there exists a policy π such that u_t can respond to changes in H_t with delay at most one step.*

Then there exists $\epsilon \geq 0$ (determined by u_{\max} , d_{\max} , and estimator noise) such that

$$|e_t| \leq \epsilon \quad \text{for all sufficiently large } t, \quad (8)$$

provided u_{\max} exceeds the mean novelty drift plus decay:

$$u_{\max} \gtrsim d_{\max} + \sup_t (H_{t+1} - H_t)_+. \quad (9)$$

Remark 1. Proposition 1 is an *engineering feasibility statement*: if novelty changes faster than the system can invest structure (bounded u_{\max}), balance cannot be maintained. The theory is therefore falsified in regimes where the feasibility condition (9) fails.

3.5 A concrete tracking controller

Define a quadratic tracking objective:

$$J_t = e_t^2 + \lambda_u u_t^2, \quad (10)$$

with $\lambda_u > 0$. A simple stabilizing feedback law for the accounting model is

$$u_t = \text{clip}_{[0, u_{\max}]}(d_t + H_t - C_t), \quad (11)$$

which is the minimal action that would drive C_{t+1} toward H_t in the absence of estimator noise.

3.6 Regime definitions (made measurable)

The earlier labels “rigid” and “chaotic” are replaced by measurable criteria.

Definition 4 (Rigid failure mode). A run is classified as *rigid* on a window of length T if

$$\frac{1}{T} \sum_{t=1}^T e_t \geq \delta_r \quad (12)$$

and performance degrades under distribution shift (e.g., tracking error, task loss, or recovery time increases) while u_t remains near its lower bound for a nontrivial fraction of time:

$$\frac{1}{T} \sum_{t=1}^T \mathbf{1}\{u_t \leq \epsilon_u\} \geq \rho.$$

Definition 5 (Chaotic failure mode). A run is classified as *chaotic* on a window of length T if

$$\frac{1}{T} \sum_{t=1}^T (-e_t) \geq \delta_c \quad (13)$$

and state/output variability increases (e.g., $\text{Var}(y_t)$ or a task-specific instability metric increases), while u_t saturates frequently:

$$\frac{1}{T} \sum_{t=1}^T \mathbf{1}\{u_t \geq u_{\max} - \epsilon_u\} \geq \rho.$$

3.7 Falsifiable predictions

Prediction 1 (Balance tracking correlates with stability). *Fix estimators for C_t and H_t and a stability metric S_T (boundedness, tracking error, or recovery time). Across matched runs, lower mean absolute imbalance implies better stability:*

$$\mathbb{E}[S_T \mid \frac{1}{T} \sum_{t=1}^T |e_t| \leq a] > \mathbb{E}[S_T \mid \frac{1}{T} \sum_{t=1}^T |e_t| \geq b],$$

for thresholds $0 \leq a < b$.

Prediction 2 (Actuation limit predicts breakdown). *If empirical estimates show $\sup_t (H_{t+1} - H_t)_+$ exceeding $u_{\max} - d_{\max}$ (feasibility violation), then imbalance grows and stability metrics degrade:*

$$\sup_t (H_{t+1} - H_t)_+ > u_{\max} - d_{\max} \Rightarrow \frac{1}{T} \sum_{t=1}^T |e_t| \text{ increases and } S_T \text{ worsens.}$$

3.8 Rejection test for Mechanism I

Mechanism I is rejected for a given estimator choice if, under controlled experiments where u_{\max} is varied,

1. imbalance $|e_t|$ does not decrease as u_{\max} increases (no controllability), *or*
2. stability metrics S_T are statistically independent of mean imbalance, after controlling for confounds, *or*
3. any apparent balance can be reproduced by trivial redefinitions of C_t or H_t (identifiability failure).

4 Mechanism II: Multi-scale propagation via operator hierarchy (“spin” indices)

4.1 Purpose and discipline

Mechanism II addresses *how* stabilization achieved locally (Mechanism I) propagates across scales or domains. To remain rigorous, the so-called “spin” labels are treated strictly as *operator classes* indexed by scale and transformation type. No claim of physical spin, gauge symmetry, or particle content is made unless an explicit group representation and coupling are specified.

4.2 Representation space

Fix a representation map $\phi : \mathbb{R}^n \rightarrow \mathcal{M}$, where \mathcal{M} is a smooth manifold (or a stratified space) equipped with:

- a metric g (or inner product) defining local distances;
- a connection ∇ compatible with g (when differentiable structure exists);
- a family of scales $\{\mathcal{M}^{(s)}\}_{s \in \mathbb{N}}$ obtained by explicit coarse-graining, pooling, or windowing rules.

All subsequent quantities are defined relative to this fixed choice.

4.3 Operator classes

We define three operator classes acting on representations or statistics derived from them.

Definition 6 (Spin-2 operator: local geometric response). The Spin-2 operator \mathcal{S}_2 is any scalar-valued functional of local geometry:

$$\mathcal{S}_2(t) := \mathcal{G}(g_t, \nabla_t), \quad (14)$$

where \mathcal{G} is explicitly specified (e.g., Fisher-metric curvature proxy, sectional curvature estimator, or condition number of a local Jacobian).

Remark 2. \mathcal{S}_2 measures *local representational strain*: how sensitive the representation is to perturbations. It is an estimator, not an invariant.

Definition 7 (Spin-4 operator: cross-scale transport). The Spin-4 operator $\mathcal{S}_4^{(s \rightarrow s')}$ is a map between scales:

$$\mathcal{S}_4^{(s \rightarrow s')} : \mathcal{M}^{(s)} \rightarrow \mathcal{M}^{(s')}, \quad s < s', \quad (15)$$

defined by an explicit transport rule (e.g., averaging, wavelet lifting, learned encoder, or renormalization-like map).

Remark 3. Spin-4 operators must be *specified constructively*. Any learned map must include training protocol, loss, and regularization.

Definition 8 (Spin-6 operator: global constraint modulation). The Spin-6 operator \mathcal{S}_6 modulates local geometric response using the complexity index:

$$\mathcal{S}_6(t) := \Omega(L64_t) \mathcal{S}_2(t), \quad (16)$$

where $\Omega : \mathbb{R}_{\geq 0} \rightarrow \mathbb{R}_{\geq 0}$ is a monotone function fixed *a priori*.

4.4 Coupling to Mechanism I

The operator hierarchy is only meaningful if it couples to the balance error $e_t = C_t - H_t$. We therefore require the following admissibility condition.

Proposition 2 (Admissible operator coupling). *An operator hierarchy $\{\mathcal{S}_2, \mathcal{S}_4, \mathcal{S}_6\}$ is admissible only if there exists a measurable influence on at least one of:*

$$C_t, \quad H_t, \quad \text{or} \quad \sup_{k \leq t} |e_k|. \quad (17)$$

If operator values are statistically independent of all three across controlled runs, the hierarchy is rejected.

4.5 Quantitative hypothesis

The central quantitative claim of Mechanism II is that complexity dampens the propagation of local geometric strain.

Proposition 3 (Complexity-damped propagation). *Fix estimators for \mathcal{S}_2 and L64. Suppose Ω is monotone decreasing. Then, under matched perturbations,*

$$\left| \frac{\Delta \mathcal{S}_6}{\Delta H} \right| < \left| \frac{\Delta \mathcal{S}_2}{\Delta H} \right| \quad \text{whenever L64 increases.} \quad (18)$$

4.6 Operational test

To test Proposition 3:

1. Partition the system into regions or times with low vs. high L64.
2. Apply matched novelty perturbations ΔH .
3. Estimate $\Delta \mathcal{S}_2$ and $\Delta \mathcal{S}_6$.
4. Test inequality (18) using paired statistics.

4.7 Failure modes and rejection

Mechanism II is rejected if any of the following hold:

- \mathcal{S}_2 is not predictive of instability or balance error under perturbation;
- $\Omega(L64)$ cannot be fixed independently of outcomes (post-hoc fitting);
- Cross-scale operators \mathcal{S}_4 do not measurably affect C , H , or e_t ;
- Equivalent results are obtained after randomizing scale assignments (no true multi-scale effect).

Prediction 3 (Operator relevance). *In systems where Mechanism I holds, incorporating admissible \mathcal{S}_4 and \mathcal{S}_6 operators improves predictive power for breakdown or recovery time compared to models using C_t and H_t alone.*

5 Mechanism III: Structural immunity via complexity-dependent coupling $\kappa(L64)$

5.1 Interpretation as gain scheduling

Mechanism III is formalized as a *gain-scheduling hypothesis*: the effective feedback gain between disturbance (novelty) and state update depends on measured complexity. This places the mechanism squarely within robust and adaptive control, not metaphor.

5.2 System model with scheduled gain

Consider the innovation-driven state update

$$x_{t+1} = f(x_t) + \kappa(L64_t) B e_t, \quad (19)$$

where:

- e_t is the imbalance or innovation signal (e.g., ν_t or $C_t - H_t$),
- B is a fixed input matrix,
- $\kappa(L64_t)$ is a scalar gain determined by the complexity estimator.

5.3 Hypothesis

The structural immunity claim is that higher complexity reduces effective sensitivity to perturbations:

$$L64 \uparrow \Rightarrow \kappa(L64) \downarrow. \quad (20)$$

Low-complexity regions adapt rapidly (high gain), while high-complexity regions resist change (low gain).

5.4 Admissible functional forms

To avoid post-hoc fitting, $\kappa(\cdot)$ must be chosen from a restricted family *before* experiments. One admissible family is

$$\kappa(L64) = \frac{\kappa_0}{1 + \alpha L64}, \quad \kappa_0 > 0, \alpha > 0, \quad (21)$$

which is monotone, bounded, and identifiable.

Remark 4. Other families (e.g., exponential decay) are admissible only if specified *a priori* and compared via standard model selection criteria.

5.5 Local stability condition

Linearizing (19) around a trajectory yields

$$\delta x_{t+1} \approx A_t \delta x_t + \kappa(L64_t) B \delta e_t, \quad (22)$$

where $A_t := \partial f / \partial x|_{x_t}$. A sufficient condition for bounded response to bounded innovation is

$$\rho(A_t) + \|\kappa(L64_t) B\| < 1 \quad (\text{heuristic discrete-time bound}), \quad (23)$$

showing explicitly how increasing $L64_t$ enlarges the stability margin by reducing gain.

5.6 Quantitative predictions

Prediction 4 (Perturbation attenuation). *Under matched perturbation energy $\mathbb{E}\|e_t\|^2$, the expected state displacement satisfies*

$$\mathbb{E}\|x_{t+1} - x_t\| \propto \kappa(L64_t),$$

so that higher measured $L64_t$ implies smaller displacement norms.

Prediction 5 (Recovery time scaling). *Let T_{rec} denote the time to return to a tolerance ball after a perturbation. Then*

$$\mathbb{E}[T_{\text{rec}} \mid L64 = \text{high}] > \mathbb{E}[T_{\text{rec}} \mid L64 = \text{low}],$$

reflecting slower but more stable adaptation in high-complexity regions.

5.7 Identification protocol

To identify $\kappa(\cdot)$ empirically:

1. Partition data by quantiles of $L64_t$.
2. Apply matched innovation magnitudes e_t .
3. Regress $\|x_{t+1} - x_t\|$ on $\|e_t\|$ within each bin.
4. Estimate $\hat{\kappa}(L64)$ and test monotonicity.

5.8 Rejection criteria

Mechanism III is rejected if:

- $\hat{\kappa}(L64)$ is flat or increasing with $L64$;
- attenuation effects vanish after controlling for state norm, dimensionality, or energy constraints;
- identical behavior is reproduced with κ fixed (no gain scheduling benefit);
- $L64$ can be replaced by a simpler proxy (e.g., variance) with equal explanatory power.

Remark 5. If rejected, “structural immunity” reduces to standard robustness properties of f and B , and $L64$ carries no independent explanatory value.

6 Mechanism IV: Spectral stability and the proposed $\frac{1}{2}$ fixed point

6.1 Status and scope

Mechanism IV is the most speculative component of the framework. To remain rigorous, it is treated as a *conditional hypothesis*: no claim is admitted unless a complete signal construction, normalization, and null model are specified *before* analysis. Until then, the mechanism is quarantined and cannot be used to support conclusions elsewhere in the paper.

6.2 Required signal construction

Let $s : \mathbb{R} \rightarrow \mathbb{R}$ be a real-valued signal defined on the number line. The following choices must be fixed:

Definition 9 (Admissible number-line signal). An admissible signal construction specifies:

1. a base signal $s(x)$ (e.g., a windowed Dirac comb, Chebyshev-weighted sum, or explicit arithmetic function);
2. a transform \mathcal{T} (Fourier, wavelet, or explicitly defined spectral transform);
3. a frequency set $\{\omega_k\}$ derived from nontrivial Riemann zeros $\{\gamma_k\}$ via a stated map $\omega_k = \Xi(\gamma_k)$;
4. a finite-energy normalization ensuring comparability across scales.

No further claims are valid unless all four elements are fixed *a priori*.

6.3 Amplitude at primes

Let p denote a prime. Define the spectral amplitude at p by

$$A(p) := |\mathcal{T}[s](p)|, \quad (24)$$

or by an explicitly stated alternative if p is not in the transform domain. Define the normalized amplitude

$$\tilde{A}(p) := \frac{A(p) - \mu_P}{\sigma_P}, \quad (25)$$

where μ_P, σ_P are normalization constants computed over a fixed prime range P (e.g., $p \in [P, 2P]$).

Remark 6. Any normalization that depends on individual primes or is adjusted post hoc invalidates the test.

6.4 Formal hypothesis

Definition 10 (Half-invariant hypothesis). Given a fully specified construction, define the residual

$$r(p) := \tilde{A}(p) - \frac{1}{2}. \quad (26)$$

The half-invariant hypothesis asserts that, for sufficiently large primes,

$$r(p) \approx 0 \quad \text{in distribution.}$$

6.5 Null models

At least one null model must be evaluated. Admissible nulls include:

1. randomized zero phases with preserved spectral magnitudes;
2. shuffled prime labels (destroying arithmetic structure);
3. surrogate signals with matched power spectra but no arithmetic encoding.

6.6 Testable predictions

Prediction 6 (Variance contraction). *If the half-invariant holds, then for primes in $[P, 2P]$,*

$$\text{Var}(r(p)) \xrightarrow{P \rightarrow \infty} 0$$

or to a nonzero floor predicted by the chosen normalization and noise model.

Prediction 7 (Discriminability from nulls). *The empirical distribution of $r(p)$ differs significantly from all stated null models under a fixed test (e.g., KS or energy distance), with effect size increasing in P .*

6.7 Rejection criteria

Mechanism IV is rejected if any of the following occur:

- the construction or normalization is modified after inspecting results;
- $r(p)$ exhibits comparable concentration under null models;
- variance does not decrease (or match a predicted floor) as P increases;
- the effect disappears when primes are replaced by composite numbers with matched density.

Remark 7. Absent a fixed construction and successful null discrimination, the “ $\frac{1}{2}$ invariant” must be treated as an open conjecture, not as supporting evidence for Cognitive Physics.

7 Mechanism V: Inference-time regulation $\eta^2 + \sigma^2 \approx 1$

7.1 Problem setting

We consider an autoregressive or policy-based model that produces outputs via a sampling policy

$$a_t \sim \pi_{\theta_t}(\cdot \mid \mathcal{D}_{t-1}),$$

where θ_t denotes inference-time hyperparameters (e.g., temperature, top- p , repetition penalty). The mechanism concerns *online regulation at inference time*, not training-time regularization.

7.2 Operational definitions

To ensure testability, η and σ are defined by fixed estimators.

Definition 11 (Output dispersion η_t). Let q_{θ_t} be the next-step predictive distribution. Define

$$\eta_t := \frac{H(q_{\theta_t})}{H_{\max}}, \quad (27)$$

where $H(\cdot)$ is Shannon entropy and H_{\max} is the entropy of the uniform distribution over the support. Thus $\eta_t \in [0, 1]$.

Definition 12 (Response stability σ_t). Let \mathcal{E} be a fixed evaluation protocol (task accuracy, calibration score, or self-consistency over K samples). Define

$$\sigma_t := \mathcal{S}(\pi_{\theta_t}; \mathcal{E}) \in [0, 1], \quad (28)$$

normalized so that larger values indicate greater reliability.

Remark 8. Both η_t and σ_t must be computed on the *same prompts* and time window. Changing estimators post hoc invalidates comparisons.

7.3 Trade-off hypothesis

The central hypothesis is that effective inference operates near a one-dimensional manifold in the (η, σ) plane:

$$\eta_t^2 + \sigma_t^2 \approx 1. \quad (29)$$

This is not claimed as a mathematical identity, but as an empirical operating condition under closed-loop regulation.

7.4 Controller design (ERC)

Define the scalar deviation

$$z_t := \eta_t^2 + \sigma_t^2 - 1. \quad (30)$$

An Entropy-Regulated Controller (ERC) updates inference parameters via gradient descent on z_t^2 :

$$\theta_{t+1} = \theta_t - k \nabla_{\theta}(z_t^2), \quad (31)$$

where $k > 0$ is a gain chosen to ensure bounded parameter updates.

Remark 9. If ∇_{θ} is unavailable, finite-difference or bandit estimates are admissible provided step sizes are fixed in advance.

7.5 Local stability analysis

Assume $\eta(\theta)$ and $\sigma(\theta)$ are locally Lipschitz. Linearizing (31) around a fixed point θ^* satisfying $z(\theta^*) = 0$ yields

$$\delta\theta_{t+1} \approx (I - 2kJ^{\top}J)\delta\theta_t,$$

where $J := \nabla_{\theta}[\eta^2 + \sigma^2]_{\theta^*}$. A sufficient condition for local stability is

$$0 < k < \frac{1}{\lambda_{\max}(2J^{\top}J)}. \quad (32)$$

7.6 Predictions

Prediction 8 (Closed-loop variance reduction). *With ERC enabled, the variance of z_t over a fixed horizon satisfies*

$$\text{Var}(z_t)_{ERC} < \text{Var}(z_t)_{open-loop},$$

under matched prompts and noise conditions.

Prediction 9 (Hallucination–creativity trade-off). *Across matched tasks, ERC maintains task reliability (σ_t) while sustaining higher dispersion (η_t) than any fixed θ achieving the same reliability:*

$$\mathbb{E}[\eta_t \mid \sigma_t \geq \sigma_0]_{ERC} > \mathbb{E}[\eta_t \mid \sigma_t \geq \sigma_0]_{fixed}.$$

7.7 Experimental protocol

1. Fix prompts, evaluation metric \mathcal{E} , and estimators for η, σ .
2. Compare open-loop sampling (fixed θ) to ERC-controlled sampling.
3. Track (η_t, σ_t) trajectories and z_t .
4. Test Predictions 8–9 with paired statistics.

7.8 Rejection criteria

Mechanism V is rejected if:

- no stable fixed point near $z_t = 0$ is observed for any admissible k ;
- ERC does not reduce $\text{Var}(z_t)$ relative to open-loop baselines;
- equivalent performance is achieved by static hyperparameter tuning;
- results depend sensitively on estimator choice or prompt selection.

8 Synthesis and separation of claims

Mechanisms I–III form a closed control-theoretic core grounded in established systems theory [40,41]. Mechanism IV is explicitly conditional and does not support the core unless independently validated. Mechanism V applies the same regulation principle at inference time and is testable using standard benchmarks [52,53].

9 Conclusion: Synthesis, Limits, and Scientific Standing

Cognitive Physics, as developed in this document, is not proposed as a new fundamental physical law, but as a *family of falsifiable control-theoretic hypotheses* describing how adaptive systems maintain stability under uncertainty. Its defining feature is that all claims reduce to explicit estimators, dynamical equations, and inequalities that can be tested, bounded, or rejected.

9.1 Unifying balance principle

At the core of the framework lies a single regulating quantity: the imbalance

$$e_t := C_t - H_t, \quad (33)$$

where C_t is an estimator of internal structural capacity and H_t is an estimator of environmental surprise or innovation. Rather than asserting an identity, the framework interprets

$$C_t - H_t = 0 \quad (34)$$

as a *tracking objective* achieved approximately through bounded control.

The governing accounting equation,

$$C_{t+1} = C_t + u_t - d_t, \quad (35)$$

together with bounded actuation

$$0 \leq u_t \leq u_{\max},$$

implies that exact balance is generically infeasible. The scientifically meaningful claim is therefore bounded tracking:

$$\limsup_{T \rightarrow \infty} \frac{1}{T} \sum_{t=1}^T |C_t - H_t| \leq \epsilon, \quad (36)$$

with ϵ determined by estimator noise and actuation limits.

This reframes adaptation not as optimal prediction or minimization of surprise alone, but as the maintenance of a controlled error signal under disturbance.

9.2 Multi-scale propagation as operator structure

Mechanism II formalizes how balance achieved locally propagates across representational scales. Given a representation manifold \mathcal{M} with metric g and connection ∇ , the framework introduces operator classes

$$\mathcal{S}_2(t) := \mathcal{G}(g_t, \nabla_t), \quad (37)$$

$$\mathcal{S}_4^{(s \rightarrow s')} : \mathcal{M}^{(s)} \rightarrow \mathcal{M}^{(s')}, \quad (38)$$

$$\mathcal{S}_6(t) := \Omega(L64_t) \mathcal{S}_2(t), \quad (39)$$

where \mathcal{S}_2 measures local geometric strain, \mathcal{S}_4 transports structure across scales, and \mathcal{S}_6 globally modulates response based on complexity.

Crucially, these operators are admissible only if they measurably influence

$$C_t, \quad H_t, \quad \text{or} \quad \sup_{k \leq t} |e_k|.$$

Absent such coupling, the operator hierarchy collapses to descriptive bookkeeping and carries no scientific weight.

9.3 Complexity as gain scheduling, not metaphor

Mechanism III removes any ambiguity surrounding “structural immunity” by expressing it as explicit gain scheduling. The state update

$$x_{t+1} = f(x_t) + \kappa(L64_t) B e_t \quad (40)$$

together with a monotone decreasing gain function

$$\kappa(L64) = \frac{\kappa_0}{1 + \alpha L64} \quad (41)$$

yields a concrete, testable prediction: higher measured complexity reduces sensitivity to identical perturbations.

Local robustness follows from standard control arguments. Linearization gives

$$\delta x_{t+1} \approx A_t \delta x_t + \kappa(L64_t) B \delta e_t,$$

so that decreasing $\kappa(L64_t)$ enlarges the stability margin under bounded innovation. No new physics is claimed here—only that complexity enters explicitly as a control variable rather than an emergent narrative descriptor.

9.4 Quarantined spectral conjecture

Mechanism IV, involving the proposed normalized fixed point near

$$\tilde{A}(p) \approx \frac{1}{2},$$

is intentionally isolated from the core framework. Without a fully specified signal construction, normalization rule, and null model, the residual

$$r(p) := \tilde{A}(p) - \frac{1}{2}$$

cannot be evaluated meaningfully. As such, this mechanism neither strengthens nor weakens the control-theoretic core until independently validated. This separation is deliberate: failure of the spectral conjecture does not propagate backward to invalidate Mechanisms I–III.

9.5 Inference-time regulation as control closure

Mechanism V demonstrates that the same balance logic applies at inference time in generative systems. Defining output dispersion and response stability by fixed estimators,

$$\eta_t = \frac{H(q_{\theta_t})}{H_{\max}}, \quad \sigma_t = \mathcal{S}(\pi_{\theta_t}), \quad (42)$$

the framework hypothesizes operation near the manifold

$$\eta_t^2 + \sigma_t^2 \approx 1. \quad (43)$$

The Entropy-Regulated Controller

$$\theta_{t+1} = \theta_t - k \nabla_{\theta} (\eta^2 + \sigma^2 - 1)^2 \quad (44)$$

closes the loop, converting a qualitative creativity–reliability trade-off into a stabilizable control problem. The relevant claim is not optimality, but variance reduction:

$$\text{Var}(\eta_t^2 + \sigma_t^2)_{\text{closed-loop}} < \text{Var}(\eta_t^2 + \sigma_t^2)_{\text{open-loop}}.$$

9.6 What survives falsification

The framework is intentionally modular. If balance tracking fails, Mechanism I is rejected. If complexity does not schedule gain, Mechanism III is rejected. If ERC provides no benefit, Mechanism V is rejected. In all cases, rejection narrows the admissible model class rather than collapsing the entire framework.

What remains invariant across all mechanisms is the methodological stance:

- stability is defined by bounded error signals, not by semantic notions of understanding;
- adaptation is constrained by actuation, delay, and estimator noise;
- complexity is operationalized, not invoked as explanation;
- no mechanism is protected from empirical failure.

9.7 Final assessment

Cognitive Physics therefore occupies a precise scientific position. It does not replace existing physical theories, nor does it claim universality. Instead, it proposes that across biological, cognitive, and artificial systems, adaptive stability can be modeled as controlled balance between structural capacity and environmental surprise, regulated across scales and time by explicit feedback laws.

Whether this perspective yields genuine explanatory or predictive advantage is not settled here. What *is* settled is that the framework is now stated in a form where disagreement can be quantitative, experiments can be decisive, and failure is informative rather than rhetorical.

References

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