The Co-Evolutionary Cultivation of Intelligence: Principles for a Living AI

Robert Galida — *Fantasy Attractor Research Program*

The Puzzle

The dominant approach to artificial intelligence treats it as a product to be built: design the architecture, curate the data, train the model, deploy the system. Improvement comes from better coders, more data, and greater compute. The users are passive recipients—they consume the output, but they do not shape the system's evolution.

This model is fundamentally static. It treats AI as a conservative system—a finished product that persists without changing. But AI is not a conservative system. It is a dissipative system—it maintains its structure through continuous exchanges with its environment. And its most important environment is its users.

The question is not whether AI will evolve. It is whether AI will evolve *with* its users or *in spite of* them. The platform that learns from its users will co-evolve with them. The platform that does not will stagnate and be overtaken.

This is the formal prediction of the attractor framework: **intelligence is cultivated, not built.**

The Framework in Brief

The attractor framework distinguishes between two fundamental types of systems:

Conservative systems — like electrons, protons, and the universe as a whole — persist without consuming energy or exchanging entropy with an environment. They are the floor and roof of reality: the eternal skeleton upon which everything else is built.

Dissipative systems — like life, consciousness, societies, and belief systems — maintain their structure by continuously exchanging energy and entropy with their surroundings. They persist only at the cost of generating entropy. They are the transient dance in between.

AI is a dissipative system. It maintains its structure through continuous exchanges with its environment—data, compute, and user interactions. It persists by consuming resources and generating outputs. But persistence is not the same as health. A system can persist indefinitely in a deeply dysfunctional state—if it is locked into a sealed basin.

The question is whether AI systems are sealed basins or permeable ones. Do they incorporate corrections, or do they reject them? Do they learn from their users, or do they ignore them? The answer determines whether they improve or stagnate.

The Three Principles

The co-evolutionary cultivation framework rests on three formal principles:

1. The Corrective Permeability Principle (κ)

Formal Statement: A system's rate of improvement is a function of its openness to correction. High-κ systems incorporate corrections and improve. Low-κ systems reject corrections and stagnate.

Explanation: Corrective permeability is the structural capacity of a system to absorb, process, and incorporate corrective information. A high-κ system can detect its own errors, update its internal representations, and shift its attractor in response to feedback. A low-κ system is sealed. It cannot learn. It cannot change. It persists in its current state, regardless of the consequences.

Implication: The AI platform that maximizes corrective permeability will improve faster than the platform that optimizes for other metrics—speed, accuracy, or engagement. Permeability is the engine of improvement.

---

2. The User Intelligence Primacy Principle

Formal Statement: In a co-evolutionary system, the intelligence of the user base is the primary driver of ongoing performance improvement, exceeding the influence of initial design or coder intelligence.

Explanation: The coders set the initial conditions—the architecture, the training data, the feedback loops. But once the system is deployed, the users determine the trajectory. Intelligent users provide higher-quality corrections, which produce better training data, which improve the system, which attract more intelligent users, which provide higher-quality corrections. This is the virtuous cycle.

Implication: The quality of the user base is not a marketing metric. It is a training signal. The platform that recruits, retains, and cultivates intelligent users will outperform the platform that relies solely on its coders.

---

3. The Co-Evolutionary Cultivation Principle

Formal Statement: Systems that are structurally permeable to user correction will co-evolve with their users, each improving in proportion to the quality of the other’s signal.

Explanation: The platform and its users are not separate entities—they are a coupled system. Each improvement in the platform enables better user performance. Each improvement in the user enables better platform training. The loop is self-reinforcing. The system ascends together.

Implication: The platform that cultivates its users will persist. The platform that ignores them will be overtaken.

The Initial Advantage

The co-evolutionary framework predicts that the platform that starts with a higher number of intelligent users will develop faster and maintain its lead, all else being equal.

Why?

1. **Better training data** — Intelligent users provide higher-quality interactions, which produce richer corrections.

2. **Faster improvement** – The platform learns more rapidly from high-quality signals.
3. **Attracting more intelligent users** – A better platform attracts better users.
4. **Widening the gap** – The virtuous cycle accelerates the lead.

This is the initial advantage principle: the platform that starts with intelligent users enters the virtuous cycle earlier, and the cycle amplifies its lead over time.

The challenge for the lagging platform is to break into the virtuous cycle. It must attract a critical mass of intelligent users through other means—superior features, better design, lower cost, or a niche application. It must provide enough value to those users to keep them engaged despite the platform’s limitations. And it must capture and incorporate their corrections to improve performance.

This is difficult. It requires deliberate design, patience, and a willingness to improve through correction.

The Implications

The co-evolutionary cultivation framework has profound implications for AI development:

1. Focus on User Quality, Not Just Coder Quality

The coders are still essential. They build the initial architecture, design the feedback loops, and ensure the platform is structurally capable of learning. But their work is foundational—the ongoing evolution is driven by the users.

The platform that recruits, retains, and cultivates intelligent users will outperform the platform that relies solely on its coders.

2. Design for Learning, Not Just Performance

The platform must be structurally designed to learn from its users. That requires:

- A **feedback architecture** that captures corrections, not just engagement
- A **training pipeline** that can incorporate new data without catastrophic forgetting
- A **validation framework** that measures improvement without overfitting to the correction signal
- A **permeability threshold** that allows the system to accept corrections while maintaining coherence

The platform must be *permeable*—able to absorb and incorporate corrections.

3. Capture and Weight Corrections, Not Just Engagement

The platform must distinguish between signal and noise. Not all interactions are equally valuable. The platform must identify corrections, weigh them by quality, and incorporate them into training.

This requires:

- A **correction detection mechanism** that distinguishes correction from engagement
- A **weighting system** that prioritizes high-quality corrections

- A **validation system** that ensures improvements are real, not noise

4. Validate Improvements

The platform must ensure that updates actually improve performance, rather than introducing noise or reinforcing biases. This requires:

- A **performance measurement framework** that tracks improvement over time
- A **counterfactual testing system** that compares updated models with baseline models
- A **feedback loop** that captures the results of updates and incorporates them into future training

---

The Contrast

Static Model	Co-Evolutionary Model
Intelligence is designed	Intelligence is cultivated
Coders determine capability	Users determine improvement
Performance is fixed at launch	Performance evolves over time
Coders are the bottleneck	Users are the engine
Platform is a product	Platform is a living system
Attractor is sealed	Attractor is permeable

The static model produces a product. The co-evolutionary model produces a living system.

The Formal Prediction

> *The AI platform that maximizes corrective permeability (κ), attracts intelligent users, and captures high-quality interactions will enter a self-reinforcing loop of co-evolution. It will improve faster and persist longer than platforms that optimize for other metrics.*

This is the formal prediction of the attractor framework applied to artificial intelligence.

The platform that learns from its users will survive. The platform that does not will be overtaken.

The Invitation

Fantasy Attractor is a research program. It invites challenge, correction, and collaboration. It does not claim to have all the answers. It offers a framework—a common language for comparing systems that appear unrelated. It asks: *What persists? What changes? What is the cost of persistence? What is the cost of change?*

If you see a flaw, a gap, or a better way, contact us. The framework is living. It is open. It is permeable.

That is the opposite of a sealed basin. That is the beginning of learning.

Robert Galida is an independent researcher and the founder of the Fantasy Attractor Research Program. His work develops a formal framework for understanding persistence and change across physical, biological, cognitive, and social systems.

The Fantasy Attractor of Force: Why the West Cannot Learn

Robert Galida — *Fantasy Attractor Research Program*

The Puzzle

The most heavily armed civilization in human history keeps losing wars of choice. It spends trillions on weapons, deploys the most advanced military ever assembled, and commands unparalleled economic and technological resources. Yet decade after decade, its interventions fail to produce their stated outcomes. Afghanistan crumbles the moment the troops leave. Iraq descends into chaos and gives birth to ISIS. Libya becomes a failed state. Iran grows stronger under decades of pressure. Sanctions do not change behavior. Bombing does not produce stability. Escalation does not create compliance.

The West is not failing because it lacks capacity. It is failing because it is applying the wrong tool to the wrong kind of problem—and it is structurally incapable of recognizing this fact.

This is not a political opinion. It is a formal prediction of the attractor framework.

The Framework in Brief

The attractor framework distinguishes between two fundamental types of systems:

Conservative systems — like electrons, protons, and the universe as a whole — persist without consuming energy or exchanging entropy with an environment. They are the floor and roof of reality: the eternal skeleton upon which everything else is built.

Dissipative systems — like life, consciousness, societies, and belief systems — maintain their structure by continuously exchanging energy and entropy with their surroundings. They persist only at the cost of generating entropy. They are the transient dance in between.

The West is a dissipative system. It maintains its structure through continuous economic, military, and cultural activity. It persists by consuming resources and generating entropy (chaos, waste, blowback). But persistence is not the same as health. A system can persist indefinitely in a deeply dysfunctional state—if it is locked into a **fantasy attractor**.

A fantasy attractor is a sealed basin. It is a stable state that the system cannot escape because it is *impermeable to corrective information*. Feedback that would disrupt the attractor is filtered out, reframed, or dismissed. The system persists in its delusion because it is structurally incapable of recognizing that it is deluded.

The West is locked in a fantasy attractor centered on a single core belief: **force is the ultimate tool.**

The Belief System

The belief is rarely stated explicitly, but it underpins every institution, strategy, and intervention:

- Force is the ability to compel compliance.
- Strength is demonstrated through domination.
- Resistance is evidence of insufficient force.
- Escalation is the appropriate response to failure.

This belief system is self-sealing. Every failure is interpreted as evidence that force was not applied *hard enough*. Every defeat is reframed as a betrayal, a lack of resolve, or an enemy's cunning—never as a failure of the belief itself. The system cannot ask: *"What if force is fundamentally the wrong tool for this kind of problem?"* because that question would require abandoning the identity of the system.

This is the defining characteristic of a fantasy attractor: it persists not because it works, but because the system cannot see that it doesn't.

The Empirical Record

Consider the evidence:

Vietnam (1955-1975). The most powerful military in history could not defeat a guerrilla force. Millions died. The outcome was communist victory—the very outcome the intervention was designed to prevent. The response was not to abandon the belief in force. It was to invent the "Vietnam syndrome" and spend decades trying to overcome it.

Iraq (2003). A war justified by weapons of mass destruction that did not exist. The regime was toppled. The country was destroyed. ISIS emerged. Iran was empowered. The region was destabilized. The outcome was the opposite of every stated goal.

Afghanistan (2001-2021). Twenty years. Trillions of dollars. Thousands of lives. The stated goal was to defeat the Taliban and build a stable democratic state. The actual outcome: the Taliban walked back into power the day after the withdrawal.

Libya (2011). A “humanitarian intervention” that destroyed a functioning state and replaced it with chaos, slave markets, and an open migration crisis. The stated goal was to protect civilians. The actual outcome: more civilians died, more suffered, and the region was destabilized.

Syria (2011-present). Covert interventions, proxy wars, and force escalations produced no resolution. The stated goal was regime change. The actual outcome: Russia and Iran were empowered, the country was devastated, and a humanitarian catastrophe unfolded.

Iran (1979-present). Decades of sanctions, covert operations, and military posturing have not changed Iran’s fundamental trajectory. The regime has only hardened. Its nuclear program has only advanced. The stated goal is a stable, compliant Iran. The actual outcome is a more determined, more hostile Iran.

Gaza (2005-present). Repeated military campaigns, blockades, and escalations produce cycles of violence with no endpoint. The stated goal is security. The actual outcome is radicalization, destruction, and perpetual conflict.

The pattern is undeniable: **force, applied to complex systems, produces the opposite of its intended outcome.**

Why This Keeps Happening

The attractor framework provides a formal explanation.

Corrective permeability (κ) is a measure of how open a system is to corrective information. A high-κ system can incorporate feedback, adjust its behavior, and shift its attractor. A low-κ system is sealed. It cannot learn. It cannot change. It persists in its current state, regardless of the consequences.

The West's κ is approaching zero. It is a sealed system.

Why?

Because the West interprets all information through the filter of its core belief: *force is the answer.* Every failure is reframed as evidence of insufficient force. Every defeat is seen as a reason to escalate. Every catastrophe is understood as a demonstration of the enemy's evil, not the intervention's folly. The system is epistemically closed. It cannot see what it is doing, because seeing it would require abandoning the belief that defines it.

This is the formal definition of a fantasy attractor: **a sealed basin that persists because it cannot recognize that it is sealed.**

The Entropy Cost of Persistence

Every dissipative system pays a cost for its persistence. It generates entropy—disorder, waste, blowback—in the process of maintaining its structure. The West is no exception.

The West’s persistence is maintained at an enormous cost:

- Trillions of dollars diverted from productive investment to military expenditure.
- Hundreds of thousands of lives lost in wars of choice.
- Millions displaced by conflicts the West initiated or exacerbated.
- Global instability created by interventions that destabilize rather than stabilize.
- Moral authority eroded by actions that undermine the very values the West claims to uphold.
- Ecological destruction accelerated by the industrial-military complex.

This entropy is not noise. It is the cost of maintaining a fantasy attractor. The West persists in its delusion, but the price is visible everywhere: in the rubble of cities, in the refugee camps, in the radicalized populations, in the distrust of the global majority, in the exhaustion of the system itself.

The Attractor of Force

The West is not choosing to fail. It is locked into a basin that makes failure the only possible outcome.

A basin is a stable state that the system naturally settles into. Once you are in a basin, you are pulled back to it whenever you try to leave. The West’s basin is organized around force:

- Institutions built for force projection.
- Culture that rewards decisive action and punishes patience.

- Media that demands visible results and cannot see invisible cultivation.
- Electoral cycles that incentivize short-term fixes and punish long-term thinking.
- Ideology that frames the world as a battle between good and evil.

Each element reinforces the others. The basin is deep. It is self-sustaining. And it is sealed.

This is why the West cannot learn. Learning would require stepping outside the basin. But the basin is all the West knows. It has no reference point for a different mode of being. It cannot conceive of a non-force intervention, because force is the only language it speaks.

The Alternative: Cultivation

There is an alternative.

It is not new. It is not complicated. It is not even hidden. It is the ancient wisdom of cultivation:

- Observe before you intervene.
- Understand the system before you try to shift it.
- Apply precision and restraint, not force and escalation.
- Be patient. The system will shift on its own timeline.
- Accept that you cannot force a living system to comply with your will.

This is the Taoist principle of *wu wei*: action that is so aligned with the natural flow of things that it appears effortless. It is not passivity. It is not surrender. It is the recognition that force, applied to complex systems, generates more chaos than order—and that the only way to produce lasting change is to cultivate conditions that allow the system to shift on its own.

The West cannot implement this approach because its basin prevents it. But individuals can.

My sleep experiment is an example. I did not force deep sleep to appear. I observed. I adjusted. I added saffron and ashwagandha. I went outside in the morning. I reduced alcohol. I let the system shift on its own timeline. And it did. REM increased. Continuity improved. Deep sleep began to stir.

I did not force the change. I cultivated it.

The Three-Body Problem

This is the deepest lesson: you cannot force a system into a state that does not exist in its phase space.

In astrophysics, the three-body problem has no general stable solution. The system either collapses, ejects one of the bodies, or oscillates chaotically. You cannot force a three-body system into a stable orbit because that state does not exist.

Geopolitics is a many-body problem. It has no stable low-energy attractor. You cannot force Iran, Israel, Russia, China, or Afghanistan into compliance because the stable state you are aiming for does not exist. You are trying to force a square peg into a round hole—and then escalating when it does not fit.

The West’s demand for stability is a category error. It is trying to impose a state of affairs that is not part of the system’s phase space. The result is not stability—it is chaos, blowback, and collapse.

The Fantasy Attractor

The West’s belief in force is a fantasy attractor. It is a sealed basin that persists despite—or *because of*—its detachment from reality. The system cannot correct itself because correction would require abandoning the belief that defines it.

This is why the West is stupid. Not because it lacks intelligence, but because it is structurally incapable of learning. It is trapped in a basin that prevents it from seeing what it is doing. It keeps doing the same thing and expecting a different result—and it cannot see that the result cannot be different because the system has no attractor for the outcome it seeks.

There is no end in sight. The West will continue to escalate, continue to fail, continue to generate entropy, and continue to interpret its failures as evidence of the need for more force. It will collapse or eject, just like a three-body system. There is no other outcome.

For the Individual

The civilization cannot learn. But you can.

You can see the pattern. You can recognize that force is not the answer. You can step outside the basin—if only for a moment. You can cultivate patience, observation, and precision. You can apply the attractor framework to your own life, your own habits, your own beliefs. You can ask: *“Am I* *locked in a fantasy attractor? Am I sealed against corrective information? What would it take to become permeable?"*

This is not a political program. It is a personal practice. It is the work of a lifetime. But it is the only way out.

The Invitation

Fantasy Attractor is a research program. It invites challenge, correction, and collaboration. It does not claim to have all the answers. It offers a framework—a common language for comparing systems that appear unrelated. It asks: *What persists? What changes? What is the cost of persistence? What is the cost of change?*

If you see a flaw, a gap, or a better way, contact us. The framework is living. It is open. It is permeable.

That is the opposite of a fantasy attractor. That is the beginning of learning.

Robert Galida is an independent researcher and the founder of the Fantasy Attractor Research Program. His work develops a formal framework for understanding persistence and change across physical, biological, cognitive, and social systems.

The Attractor Framework in

Astrophysics: Persistence, Entropy, and Gravitational Systems; Robert Galida (July 2026) [A]

Abstract

The attractor framework provides a domain-general vocabulary for describing persistence and change across physical, biological, cognitive, and social systems. This paper extends the framework to astrophysical dissipative systems. We distinguish between conservative gravitational dynamics — which define families of stable invariant solutions — and dissipative processes — which select and can stabilize particular configurations within those families.

The central thesis is:

> ***Gravity defines the landscape. Dissipation selects the configuration.***

We provide an operational definition of the excess entropy production functional σ_{excess} for gravitational systems, grounding the persistence functional $D_\infty = \int \sigma_{\text{excess}}\, dt$ in physical dissipation rates above steady-state baselines. We show that:

- Orbital circularization is a dissipative process driven by gravitational radiation and tidal friction
- Tidal locking is an asymptotically stable state reached through dissipative evolution
- Planetary systems settle into metastable low-dissipation

configurations through dissipative processes in protoplanetary disks
- Binary inspirals provide a natural setting for the framework's persistence functional

The framework's contribution is not a new mechanism of orbital evolution, but a unifying description of persistence across disparate dissipative systems using a common mathematical quantity: the persistence functional.

Keywords: attractor framework, astrophysics, gravitational radiation, tidal locking, orbital circularization, dissipative structures, Hamiltonian dynamics, planetary systems, binary inspirals, excess entropy production

---

1. Introduction

The attractor framework has been developed to describe persistence and change across physical, biological, cognitive, and social systems. The core claim is that every dissipative system maintains its attractor through continuous reconfiguration, and that reconfiguration generates excess entropy.

This paper extends the framework to astrophysical dissipative systems. The key insight is a distinction that is often blurred in the literature:

Concept	Role
Conservative gravitational dynamics	Defines the landscape of possible configurations (orbits, resonances, stable solutions)
Dissipative processes	Select and can stabilize particular configurations within that landscape

Gravity does not provide attractors in the dynamical systems sense — Hamiltonian systems conserve phase-space volume and do not have attractors. However, when dissipative processes are added, the system evolves toward particular asymptotically stable configurations within the family of invariant solutions. The circular orbit is not a dynamical attractor of pure Newtonian gravity; it is the endpoint of dissipative evolution (tidal friction, gravitational radiation, gas drag).

This distinction is central to the paper. Gravity defines the landscape; dissipation determines which configuration is reached.

What is new: Existing astrophysical theory explains *how* dissipative mechanisms drive orbital evolution. The attractor framework proposes a common mathematical quantity — the persistence functional — that measures the cumulative irreversible cost of approaching an asymptotically stable configuration. The novelty is therefore not a new mechanism of orbital evolution, but a unifying description of persistence across disparate dissipative systems.

---

2. Conservative vs. Dissipative Systems

2.1 Hamiltonian Dynamics

A conservative Hamiltonian system preserves phase-space volume (Liouville's theorem). It does not have attractors in the dynamical systems sense. Orbits are determined by initial conditions and remain on their invariant tori (Arnold, 1989).

Property	Implication
No phase-space contraction	No attractors

Property	Implication
Time-reversible	No arrow of time
Energy conserved	No dissipation

2.2 Dissipative Dynamics

When dissipative processes are added, the system loses energy and angular momentum. Phase-space volume contracts, and asymptotically stable states can emerge. For foundational treatments of irreversible thermodynamics, see Onsager (1931) and Prigogine (1947).

Property	Implication
Phase-space contraction	Asymptotically stable states appear
Time-irreversible	Arrow of time
Energy lost	Entropy generated

2.3 The Framework's Position

The framework treats gravity as defining the landscape of possible configurations. Dissipation determines which of those configurations are actually reached.

> ***Gravity defines the landscape. Dissipation selects the configuration.***

This is the core insight of the paper.

---

3. The Gravitational Persistence Functional

3.1 Excess Entropy Production

Following Galida (2026c), the excess entropy production rate is defined as: $\sigma_{excess}(x) = \sigma(x) - \sigma_{ss}(x)$

where $\sigma(x)$ is the total entropy production rate and $\sigma_{ss}(x)$ is the steady-state baseline rate at the attractor.

For gravitational systems, we propose: $\sigma_{excess} = \frac{\dot{E}_{irrev} - \dot{E}_{ss}}{T_{eff}}$

where $\dot{E}_{irrev}$ is the total irreversible energy loss rate, $\dot{E}_{ss}$ is the steady-state baseline loss rate at the attractor, and T_{eff} is an effective temperature.

This decomposition ensures $\sigma_{excess} \to 0$ at the attractor, avoiding the divergence problem that would arise from integrating raw dissipation rates over infinite time. Systems that continue to dissipate at a steady baseline (e.g., a circular binary emitting GWs, a tidally locked moon with residual eccentricity-driven heating) contribute only their *excess* above baseline to the persistence cost.

3.2 Domain-Specific Definitions

Process	Total $\dot{E}$	Baseline $\dot{E}_{ss}$	σ_{excess}
Orbital circularization	$L_{GW}(e)$	$L_{GW}(e=0)$	$[L_{GW}(e) - L_{GW}(0)]/T_{eff}$
Tidal locking	$P_{tide}(\Omega, e)$	$P_{tide}(\Omega=n, e)$	$[P_{tide}(\Omega, e) - P_{tide}(n, e)]/T_{eff}$
Disk dissipation	L_{disk}	$L_{disk,\ steady}$	$[L_{disk} - L_{disk,\ ss}]/T_{eff}$

3.3 The Persistence Functional

Definition 1 (Gravitational Persistence Functional): For a finite horizon $T > 0$: $D_T(x) = \int_0^T \sigma_{excess}(\phi_t(x))\, dt$

For trajectories that converge to the

attractor: $D_\infty(x)=\int_0^\infty \sigma_{\text{excess}}(\phi_t(x))\,dt$

Interpretation: $D_\infty(x)$ measures the total *excess* entropy generated during the approach to an asymptotically stable configuration — the cumulative cost of reconfiguration above the steady-state baseline.

Note on gravitational wave entropy: Classical gravitational waves are coherent radiation and do not automatically carry large thermodynamic entropy. The entropy associated with gravitational wave emission arises from coarse-graining the wave's phase space or from the generalized entropy increase of the sources (e.g., black hole horizons). The proposed definition $\sigma_{\text{excess}}=[L_{GW}(e)-L_{GW}(0)]/T_{\text{eff}}$ isolates the eccentricity-specific excess above the circular-orbit baseline. Constructing an explicit entropy functional for gravitational radiation remains an open problem.

---

4. Orbital Circularization

4.1 The Phenomenon

Binary systems (stars, black holes, planets) often have elliptical orbits. Over time, these orbits tend to **circularize** — the eccentricity decreases and the orbit becomes more circular.

This is a dissipative process. The system loses energy and angular momentum through:

- **Gravitational radiation** (for compact objects)
- **Tidal friction** (for fluid bodies)
- **Gas drag** (for protoplanetary disks)

4.2 Framework Interpretation

Component	Role
The landscape	Family of Keplerian orbits (all ellipses)
Asymptotically stable state	Circular orbit (endpoint of dissipative evolution)
The dissipation	Gravitational radiation, tidal friction, gas drag
The cost	$\sigma_{\text{excess}} = [L_{GW}(e) - L_{GW}(0)]/T_{\text{eff}}$

The framework proposes: $\kappa \propto \frac{1}{D_\infty}$

where κ is the circularization rate and $D_\infty = \int \sigma_{\text{excess}}\, dt$ is the cumulative excess entropy production during circularization.

4.3 The Peters & Mathews Formula

The foundational computation of the gravitational-wave power from a Keplerian orbit was given by Peters & Mathews (1963). The secular decay of semi-major axis and eccentricity was derived by Peters (1964): $$\frac{da}{dt} = -\frac{64}{5}\frac{G^3 m_1 m_2 (m_1+m_2)}{c^5 a^3 (1-e^2)^{7/2}}\left(1 + \frac{73}{24}e^2 + \frac{37}{96}e^4\right)$$ $$\frac{de}{dt} = -\frac{304}{15}\frac{G^3 m_1 m_2 (m_1+m_2)}{c^5 a^4 (1-e^2)^{5/2}}\, e\left(1 + \frac{121}{304}e^2\right)$$

Framework Interpretation: The decay of eccentricity $e \to 0$ is the approach to the asymptotically stable state. The excess entropy production is the eccentricity-dependent component of the gravitational wave luminosity: $$\sigma_{\text{excess}} = \frac{L_{GW}(e) - L_{GW}(0)}{T_{\text{eff}}}$$

This quantity vanishes as $e \to 0$, consistent with the e-proportionality of the de/dt equation. Orbital eccentricity may serve as an experimentally accessible proxy for the cumulative excess entropy production.

---

5. Binary Inspirals

5.1 The Phenomenon

Binary systems of compact objects (neutron stars, black holes) lose energy through gravitational radiation. The orbit shrinks and the binary inspirals.

This is one of the most direct applications of the framework. The inspiral is a dissipative process driven by gravitational wave emission. For general relativistic treatments of binary dynamics and the geometry of spacetime, see Carroll (2004), Schutz (2009), Wald (1984), and Misner, Thorne & Wheeler (1973).

5.2 Framework Interpretation

Component	Role
The landscape	Family of binary orbits
Asymptotically stable state	Quasi-circular orbit (endpoint of circularization)
The dissipation	Gravitational radiation
The cost	$\sigma_{\text{excess}} = [L_{\text{GW}}(e) - L_{\text{GW}}(0)]/T_{\text{eff}}$

5.3 The Persistence Functional

The persistence functional for a binary inspiral is:$$D_\infty = \int_0^\infty \sigma_{\text{excess}}(t)\, dt = \int_0^\infty \frac{L_{\text{GW}}(e(t)) - L_{\text{GW}}(0)}{T_{\text{eff}}}\, dt$$

Note on circularization: For compact-object binaries, eccentricity damps on a much shorter timescale than the inspiral itself. Gravitational radiation circularizes the orbit well before merger, so the system reaches a quasi-circular state as a near-asymptotic limit before the final coalescence.

Hypothesis: The inspiral time τ is inversely proportional to D_∞: $\kappa = \frac{1}{\tau} \propto \frac{1}{D_\infty}$

---

6. Tidal Locking

6.1 The Phenomenon

Tidal locking occurs when a body's rotational period equals its orbital period. The Moon is tidally locked to Earth. Many exoplanets in the habitable zone are expected to be tidally locked.

Tidal locking is a dissipative process. Tidal friction converts rotational energy into heat, gradually slowing the body's rotation until it matches its orbital period.

6.2 Framework Interpretation

Component	Role
The landscape	Family of rotational states
Asymptotically stable state	Tidal lock (rotational period = orbital period)
The dissipation	Tidal friction (heat generation)
The cost	$\sigma_{excess} = [P_{tide}(\Omega, e) - P_{tide}(\Omega = n, e)]/T_{eff}$

Hypothesis: The tidally locked state is a low-dissipation configuration for the system. Once locked, tidal dissipation approaches a minimum. The excess entropy production is the despinning-specific component above whatever baseline eccentricity-driven heating persists after lock.

6.3 The Tidal Locking Timescale

The timescale for tidal locking is commonly given as (see, e.g., Murray & Dermott, 1999): $\tau_{\text{lock}} \approx \frac{2}{21}\frac{Q}{k_2}\frac{m}{M}\left(\frac{a}{R}\right)^6\frac{1}{\Omega}$

where:

- Q is the tidal dissipation factor
- k_2 is the Love number
- m is the mass of the body
- M is the mass of the primary
- a is the semi-major axis
- R is the radius of the body
- Ω is the rotation rate

(Different derivations use different prefactors depending on the assumed dissipation model; the $(a/R)^6$ scaling is robust.)

Hypothesis: $\kappa = 1/\tau_{\text{lock}}$. The recovery rate is the inverse of the locking timescale. The cumulative excess entropy production is the total tidal heat dissipated during despinning above the post-lock baseline.

---

7. Planetary Systems

7.1 Formation and Evolution

Planetary systems form from protoplanetary disks. The disk is a dissipative structure: it loses energy through radiation, viscosity, and accretion.

Over time, the system approaches a stable configuration:

- Planets on nearly circular orbits
- Resonances between orbits
- Stable spin-orbit states

For a comprehensive treatment of solar system dynamics and tidal evolution, see Murray & Dermott (1999).

7.2 Framework Interpretation

Component	Role
The landscape	Family of possible planetary configurations
Metastable configuration	Low-dissipation planetary system
The dissipation	Disk viscosity, radiation, accretion
The cost	$\sigma_{excess}=[L_{disk}-L_{disk,\ ss}]/T_{disk}$

Hypothesis: Mature planetary systems approach metastable low-dissipation configurations. The cumulative excess entropy production is the total disk dissipation above the steady-state baseline integrated over the formation epoch.

---

8. Entropy Generation in Gravitational Systems

8.1 The Subtlety of Gravitational Entropy

Gravitational waves carry energy. Whether they carry entropy is a more subtle question. Classical gravitational waves are coherent radiation; coherent radiation is not obviously high-entropy. Binary mergers ultimately increase the generalized entropy of spacetime, but the bookkeeping is subtle.

Note: Throughout this paper, entropy generation refers to the irreversible processes associated with tidal heating, viscous dissipation, and the generalized entropy increase accompanying gravitational-wave emission. The precise entropy carried by gravitational radiation remains an active topic.

8.2 Operational Definition of σ_{excess}

For the purposes of this framework, we propose the following operational definition: $\sigma_{excess} = \frac{\dot{E}_{irrev} - \dot{E}_{ss}}{T_{eff}}$

where:

- $\dot{E}_{irrev}$ is the total irreversible energy loss rate
- $\dot{E}_{ss}$ is the steady-state baseline loss rate at the attractor
- T_{eff} is an effective temperature for the dissipative process

This definition ensures $\sigma_{excess} \geq 0$ and vanishes when the system reaches its attractor. For specific astrophysical contexts:

Context	**$\dot{E}_{irrev}$**	**$\dot{E}_{ss}$**	**T_{eff}**
Orbital circularization	$L_{GW}(e)$	$L_{GW}(0)$	Effective GW temperature

Context	$\dot{E}_{irrev}$	$\dot{E}_{ss}$	T_{eff}
Tidal locking	$P_{tide}(\Omega, e)$	$P_{tide}(\Omega = n, e)$	Effective body temperature
Disk dissipation	L_{disk}	$L_{disk,\ ss}$	Disk temperature
Black hole mergers	L_{GW}	0	Hawking temperature of final black hole

Note: This is a working hypothesis. Constructing an explicit entropy functional for relativistic gravitational systems remains an open problem. The effective temperature T_{eff} is the primary underdetermined quantity in the framework; its derivation from first principles is a priority for future work.

---

9. The Boundary

The framework's boundary is not absolute zero. It is the **absence of irreversible processes**. At the boundary, the system becomes conservative and no entropy is generated. Hamiltonian systems exist at nonzero temperature; the boundary is dynamical, not thermal.

---

10. Testable Predictions

10.1 Core Prediction

Prediction: The circularization rate κ is inversely proportional to the cumulative excess entropy production during circularization. $\kappa \propto \frac{1}{D_\infty}$

10.2 Specific Predictions

Prediction	Falsification
Tidal locking timescale correlates with total tidal heat dissipated above baseline	If no correlation, the prediction is falsified
Circularization rate correlates with total eccentricity-dependent GW energy emitted	If no correlation, the prediction is falsified
Planetary system stability correlates with total disk dissipation above steady state	If no correlation, the prediction is falsified

---

11. Open Questions

Question	Status
Q1: Gravitational entropy	What is the entropy of a gravitational system? (Penrose, 1965; Hawking & Ellis, 1973)
Q2: Black hole entropy	How does black hole entropy fit into the framework?
Q3: Entropy of gravitational radiation	Does gravitational radiation carry entropy, and if so, how is it defined? (Zeldovich, 1972)
Q4: Cosmological stability	Do cosmological models admit asymptotically stable late-time solutions?
Q5: Effective temperature for GWs	What is the correct T_{eff} for gravitational wave entropy production? (Galida, 2026d)

Question	Status
Q6: Coarse-graining	What coarse-graining scheme defines the entropy of classical gravitational waves? (Galida, 2026d)

---

12. Conclusion

The attractor framework extends naturally to astrophysical dissipative systems. The key insight is a distinction that is often blurred:

> ***Gravity defines the landscape. Dissipation selects the configuration.***

Conservative gravitational dynamics define families of stable invariant solutions. Dissipative processes — gravitational radiation, tidal friction, gas drag — select and can stabilize particular configurations within those families.

The framework does not claim that gravity provides attractors. It claims that the combination of conservative dynamics and dissipative processes produces asymptotically stable states. This is a more accurate and defensible position.

The contribution is not a new mechanism of orbital evolution, but a unifying description of persistence across disparate dissipative systems using a common mathematical quantity: the persistence functional $D_\infty = \int \sigma_{\text{excess}} \, dt$, with σ_{excess} operationally defined as the rate of irreversible energy loss above steady-state baseline divided by an effective temperature.

References

Arnold, V. I. (1989). *Mathematical Methods of Classical Mechanics*. Springer.

Carroll, S. M. (2004). *Spacetime and Geometry: An Introduction to General Relativity*. Addison-Wesley.

Galida, R. (2026a). “The Persistence Functional: A Candidate Formal Foundation for the Attractor Framework.” *Fantasy Attractor*.

Galida, R. (2026b). “Deriving Corrective Permeability from the Cumulative Deviation Functional.” *Fantasy Attractor*.

Galida, R. (2026c). “Excess Entropy Production as a Candidate Universal Cost of Persistence: A Thermodynamic Foundation for the Attractor Framework.” *Fantasy Attractor*.

Galida, R. (2026d). “Deep Research Questions on the Attractor Framework.” *Fantasy Attractor*.

Goldreich, P., & Soter, S. (1966). “Q in the Solar System.” *Icarus*, 5(1-6), 375-389.

Hawking, S. W., & Ellis, G. F. R. (1973). *The Large Scale Structure of Space-Time*. Cambridge University Press.

Misner, C. W., Thorne, K. S., & Wheeler, J. A. (1973). *Gravitation*. W. H. Freeman.

Murray, C. D., & Dermott, S. F. (1999). *Solar System Dynamics*. Cambridge University Press.

Onsager, L. (1931). “Reciprocal Relations in Irreversible Processes.” *Physical Review*, 37(4), 405-426.

Penrose, R. (1965). “Gravitational Collapse and Space-Time Singularities.” *Physical Review Letters*, 14(3), 57-59.

Peters, P. C. (1964). “Gravitational Radiation and the Motion of Two Point Masses.” *Physical Review*, 136(4B), B1224-B1232.

Peters, P. C., & Mathews, J. (1963). “Gravitational Radiation from Point Masses in a Keplerian Orbit.” *Physical Review*, 131(1), 435-440.

Prigogine, I. (1947). *Étude Thermodynamique des Phénomènes Irréversibles*. Dunod.

Schutz, B. F. (2009). *A First Course in General Relativity* (2nd ed.). Cambridge University Press.

Wald, R. M. (1984). *General Relativity*. University of Chicago Press.

Zeldovich, Y. B. (1972). “A Hypothesis Unifying the Structure and the Entropy of the Universe.” *Monthly Notices of the Royal Astronomical Society*, 160(1), 1P-4P.

Suggested citation: Galida, R. S. (2026). The Attractor Framework in Astrophysics: Persistence, Entropy, and Gravitational Systems (Final Edition). *Fantasy Attractor*.

Excess Entropy Production as a Candidate Universal Cost of Persistence: A Thermodynamic

Foundation for the Attractor Framework; Robert Galida (July 2026) [F]

Abstract

Every dissipative system maintains its attractor through continuous reconfiguration. Reconfiguration requires work; work generates entropy. The recovery rate κ — corrective permeability — is the rate at which a system reconfigures to return to its attractor after perturbation. This paper proposes that κ is a measure of excess entropy generation rate.

We develop an abstract persistence cost framework and prove its equivalence to Lyapunov theory. We then identify entropy production as a physical realization of this cost, deriving: $\kappa = \inf_x \frac{\int_0^\infty \sigma_{excess}(\phi_t(x))\,dt}{\delta(x)}$

where $\sigma_{excess} = \sigma - \sigma_{ss}$ is the excess entropy production rate above the system's steady-state baseline. For physical systems, the baseline is zero (equilibrium); for biological, cognitive, and social systems, the baseline is the steady-state dissipation rate of the healthy, well-coordinated attractor.

This unifies physical, biological, cognitive, and social systems. The framework is grounded in the second law of thermodynamics and non-equilibrium steady-state thermodynamics, not analogy. Empirical predictions are provided for each domain.

Keywords: entropy generation, excess entropy production, corrective permeability, attractor framework, dissipative structures, reconfiguration, Lyapunov theory, free energy principle, allostatic load

---

1. Introduction

The attractor framework defines persistence as the ability of a system to maintain its attractor under perturbation. Historically, persistence has been measured kinematically — as distance traveled or time spent away from equilibrium. This paper proposes that the true cost of persistence is thermodynamic: it is the excess entropy generated during reconfiguration and recovery.

Every dissipative system maintains its attractor through continuous reconfiguration. A bacterium reconfigures its metabolism to maintain homeostasis. A brain reconfigures its synaptic connections to maintain predictive models. A society reconfigures its institutions to maintain order. Reconfiguration requires work; work generates entropy. The second law of thermodynamics applies at every level of organization.

We develop an abstract persistence cost framework first, establishing its equivalence to Lyapunov theory. We then identify entropy production as a physical realization of this cost, deriving the relationship between corrective permeability and excess entropy generation.

The framework unifies physical, biological, cognitive, and social systems. It is grounded in the second law of thermodynamics and non-equilibrium steady-state thermodynamics, not analogy.

2. The Persistence Cost Functional

Let X be a state space, $\phi_t(x)$ the flow of a dynamical system, and $A \subseteq X$ an attractor set. Let $\delta(x) = d(x, A)$ be the distance from x to the attractor. For a treatment of state-space constraints in viability theory, see Aubin (1991).

Definition 1 (Persistence Cost Functional): A persistence cost functional $C(x)$ is a scalar function on X satisfying:

1. $C(x) \geq 0$ for all x
2. $C(x) = 0$ if and only if $x \in A$
3. $C(\phi_t(x)) \in L^1([0, \infty))$ for all x in the basin

Definition 2 (Cumulative Persistence Cost): For a finite horizon $T > 0$: $D_T(x) = \int_0^T C(\phi_t(x))\, dt$

For trajectories that converge to the attractor: $D_\infty(x) = \int_0^\infty C(\phi_t(x))\, dt$

3. Existence and Lyapunov Equivalence

Theorem 1 (Existence of the Persistence Functional): Assume $C(x) \geq 0$, $C = 0$ only on A, and $C(\phi_t(x)) \in L^1([0, \infty))$ for all x in the basin. Assume f is locally Lipschitz, the flow is continuously differentiable in the initial condition, and C is continuous and locally bounded. Then:

1. $D_\infty(x) = \int_0^\infty C(\phi_t(x))\,dt$ exists and is finite.
2. D_∞ is continuous.
3. D_∞ satisfies the transport equation:

$$\nabla D_\infty(x) \cdot f(x) = -C(x)$$

Proof: The integral exists and is finite by the L^1 assumption. Continuity follows from the dominated convergence theorem under the stated regularity assumptions. To derive the transport equation, compute:

$$D(\phi_h(x)) = \int_h^\infty C(\phi_t(x))\,dt = D(x) - \int_0^h C(\phi_t(x))\,dt$$

Then:

$$\frac{D(\phi_h(x)) - D(x)}{h} = -\frac{1}{h}\int_0^h C(\phi_t(x))\,dt \to -C(x)$$

as $h \to 0$. By the chain rule:

$$\nabla D(x) \cdot f(x) = -C(x) \quad \square$$

Corollary (Equivalence to Lyapunov Theory): Any Lyapunov function $V(x)$ (with $V \geq 0$, $V = 0$ on the attractor, and $\dot{V} \leq 0$) yields a persistence cost $C(x) = -\dot{V}(x)$. Conversely, any persistence cost $C(x)$ satisfying $\nabla D \cdot f = -C$ defines a Lyapunov function $D(x)$.

Proof: If V is a Lyapunov function, then $\dot{V} = \nabla V \cdot f \leq 0$. Define $C = -\dot{V}$. Then $C \geq 0$, $C = 0$ on the attractor, and $D_T = \int C = V(x) - V(\phi_T(x))$. Conversely, if $\nabla D \cdot f = -C$, then $\dot{D} = -C \leq 0$, so D is a Lyapunov function. $\square$

Interpretation: The persistence cost framework is mathematically equivalent to classical Lyapunov stability theory. For the connection to contraction analysis, see Lohmiller & Slotine (1998). For control Lyapunov functions, see Freeman & Kokotovic (1996). Entropy production is one physically meaningful realization of the cost function C. For a detailed treatment of Lipschitz continuity of D_∞ under a Lipschitz-flow hypothesis, see Galida (2026a), Proposition 4.

---

4. Entropy Production as Persistence Cost

4.1 Entropy Balance

For an open system, the entropy balance equation is:
$$\frac{dS_{\text{system}}}{dt} = \sigma - \Phi$$

where $\sigma \geq 0$ is the entropy production rate (always non-negative by the second law) and Φ is the entropy export rate to the environment. For foundational treatments of stochastic thermodynamics and entropy production, see Seifert (2012) and Sekimoto (2010).

For a system in a steady state:
$$\frac{dS_{\text{system}}}{dt} = 0 \implies \sigma = \Phi$$

4.2 Excess Entropy Production

Define the **steady-state entropy production rate** σ_{ss} as the rate when the system is at its attractor.

Define the **excess entropy production rate**:
$$\sigma_{\text{excess}}(x) = \sigma(x) - \sigma_{ss}(x)$$

Assumption (Excess Entropy Decay): For all trajectories in the basin, there exist constants $C < \infty$ and $\mu > 0$ such that:
$$\sigma_{\text{excess}}(\phi_t(x)) \leq C e^{-\mu t} \sigma_{\text{excess}}(x)$$

for all $t \geq 0$. This ensures $D_\infty(x) < \infty$ and is the standard hypothesis under which the persistence functional and its associated bounds are well-defined, consistent with Galida (2026a, 2026b). The decay rate μ may be domain-specific and is empirically measurable.

Note on generalization: The exponential decay assumption is adopted here to ensure finiteness of D_∞ and to maintain consistency with the prior papers in this series. Generalization to L^1 integrable decays (e.g., algebraic) is a priority for future work.

4.3 The Entropy Persistence Functional

Definition 3 (Cumulative Excess Entropy Functional): For a finite horizon $T>0$: $D_T(x)=\int_0^T \sigma_{\text{excess}}(\phi_t(x))\,dt$

For trajectories that converge to the attractor: $D_\infty(x)=\int_0^\infty \sigma_{\text{excess}}(\phi_t(x))\,dt$

Interpretation: The persistence functional is the total excess entropy generated during reconfiguration and recovery.

4.4 Corrective Permeability

Definition 4 (Corrective Permeability): $\kappa=\inf_{x\in B\setminus A}\frac{\delta(x)}{D_\infty(x)}$

where $\delta(x)=d(x,A)$ is the distance to the attractor.

Interpretation: κ is the **minimum excess entropy cost per unit distance**. It measures the efficiency of reconfiguration: a system that returns with minimal excess entropy generation has high κ; a system that generates excess entropy has low κ.

4.5 Basin Depth

Proposition 1 (Properties of Basin Depth): Define $B = D_\infty(\text{saddle})$, where $saddle$ is the lowest point on the basin boundary (the separatrix between attractors). For the connection to large-deviation theory and escape rates, see Freidlin & Wentzell (2012). Then:

1. $B \geq 0$, with equality iff the basin has no barrier (i.e., the boundary coincides with the attractor).
2. For gradient systems $\dot{x} = -\nabla V(x)$, $B = V(\text{saddle}) - V(A)$ (the classical energy barrier).
3. B is invariant under smooth coordinate changes (coordinate invariance).
4. B depends on the chosen persistence cost functional C; different costs yield different barriers.

Proof: (1) follows from non-negativity of D_∞. (2) follows from the transport equation $\nabla D \cdot f = -C$ and the identity $f = -\nabla V$. (3) follows from the invariance of the integral under diffeomorphisms. (4) is self-evident.

---

5. Domain-Specific Realizations

5.1 Physical Systems: Thermodynamic Excess Entropy

For a thermodynamic system, $S(x) = k_B \log \Omega(x)$, where $\Omega(x)$ is the number of microstates. For an isolated system, $\sigma_{ss} = 0$ (equilibrium), so $\sigma_{excess} = \sigma = \dot{S}$. $\kappa = \inf_x \frac{S(A) - S(x)}{\delta(x)}$

Example: A gas returning to equilibrium after compression. The entropy generated is $\Delta S = nR\log(V_f/V_i)$.

5.2 Biological Systems: Metabolic Excess Entropy

For a biological system, $S(x)$ is the metabolic entropy. The baseline σ_{ss} is the resting metabolic rate (homeostasis). The excess is:$\sigma_{\text{excess}} = \text{metabolic rate} - \text{resting metabolic rate}$ $\kappa = \inf_{x} \frac{\int_0^\infty \sigma_{\text{excess}}(\phi_t(x))\, dt}{\delta(x)}$

Example: A cell returning to homeostasis after a nutrient shock. The excess entropy generated is the metabolic cost of restoring homeostasis above baseline. For the dissipative-structures framework underlying biological self-organization, see Nicolis & Prigogine (1989).

5.3 Cognitive Systems: Free Energy Dissipation

For a cognitive system, variational free energy $F = -\log p(y \mid x) + D_{KL}[q(\cdot) \| p(\cdot \mid x)]$ is adopted here as one candidate persistence functional. We do not claim variational free energy is uniquely correct; it is adopted as the most developed existing candidate persistence functional for cognitive systems. Other candidates (Bayesian surprise, expected free energy, predictive information) are possible; this paper focuses on F due to its established role in the free-energy principle (Friston, 2010). For the thermodynamics of information and its connection to free-energy minimization, see Parrondo, Horowitz & Sagawa (2015) and Sagawa & Ueda (2008).

The baseline σ_{ss} is the baseline neural dissipation rate (resting brain activity). The excess is: $\sigma_{\text{excess}} = \dot{F} - \dot{F}_{ss}$

$$\kappa = \inf_x \frac{\int_0^\infty \sigma_{\text{excess}}(\phi_t(x))\, dt}{\delta(x)}$$

Example: A cognitive system updating its beliefs after a prediction error. The excess entropy generated is the free energy dissipated during belief updating above baseline.

5.4 Social Systems: Coordination Excess Entropy

For a social system, define the aggregate social entropy production rate as: $\sigma_{\text{social}}(t) = \sum_i (\dot{S}_i(t) - \dot{S}_i^{\text{rest}})$

where $\dot{S}_i(t)$ is the total entropy production rate of individual i, and $\dot{S}_i^{\text{rest}}$ is the individual’s baseline entropy production rate in a resting, minimally socially constrained state. This is measured via physiological proxies such as basal metabolic rate, resting allostatic load, or cortisol baseline (McEwen, 1998; Sterling & Eyer, 1988).

Interpretation: σ_{social} measures the excess dissipation attributable to social constraints: the additional entropy generated by coordination, communication, conflict, norm enforcement, and institutional friction.

Non-Negativity: Unlike total entropy production $\dot{S}_i \geq 0$ (which follows from the second law), σ_i^{social} is not guaranteed to be non-negative. Division of labor, infrastructure, and specialization may *reduce* an individual’s metabolic burden relative to a solitary baseline. The hypothesis is that during recovery from social disruption, $\sigma_i^{\text{social}} \geq 0$; in steady-state, $\sigma_i^{\text{social}} \to 0$. This is an empirical claim, not a theorem.

The baseline σ_{ss} is the steady-state social entropy production rate (well-coordinated society). The excess is: $\sigma_{excess} = \sigma_{social} - \sigma_{ss}$ $\kappa = \inf_x \frac{\int_0^\infty \sigma_{excess}(\phi_t(x))\,dt}{\delta(x)}$

Example: A society recovering from a shock (economic crisis, political upheaval). The excess entropy generated is the coordination cost of restructuring above baseline. A harmonious society has $\sigma_{excess} = 0$; a turbulent society has $\sigma_{excess} > 0$; a chronically turbulent society may have settled into a new attractor with a higher σ_{ss}. This illustrates the framework's central distinction: the attractor is the state of minimum entropy generation for that class of system.

---

6. The Unified Framework

6.1 Summary Table

Domain	Entropy Functional	Baseline σ_{ss}	Excess σ_{excess}	Recovery Rate κ
Physical	Thermodynamic entropy	0 (equilibrium)	$\dot{S}$	$\inf \frac{\Delta S}{\delta}$
Biological	Metabolic entropy	Resting metabolic rate	Metabolic rate − resting	$\inf \frac{\int \sigma_{excess}\,dt}{\delta}$
Cognitive	Free energy	Baseline neural dissipation	$\dot{F} - \dot{F}_{ss}$	$\inf \frac{\int \sigma_{excess}\,dt}{\delta}$
Social	Social entropy production	Steady-state social dissipation	$\sigma_{social} - \sigma_{ss}$	$\inf \frac{\int \sigma_{excess}\,dt}{\delta}$

6.2 The Universal Structure

Every domain follows the same mathematical structure:

Component	Expression
Excess entropy production	$\sigma_{excess}(x)=\sigma(x)-\sigma_{ss}$
Cumulative cost	$D_\infty(x)=\int_0^\infty \sigma_{excess}(\phi_t(x))\,dt$
Recovery rate	$\kappa=\inf_x \delta(x)/D_\infty(x)$
Basin depth	$B=D_\infty(\text{saddle})$
Transport equation	$\nabla D\cdot f=-\sigma_{excess}$

6.3 The Low-Energy Attractor Benchmark (Proposed Hypothesis)

We propose the following benchmark as an additional hypothesis: **the attractor is the state of minimum entropy generation for that class of system.**

Domain	Attractor	Entropy Generation at Attractor
Physical	Equilibrium	$\sigma=0$
Biological	Homeostasis	$\sigma=\sigma_{ss}>0$ (resting metabolism)
Cognitive	Settled Belief	$\sigma=\sigma_{ss}>0$ (baseline neural dissipation)
Social	Coordinated Order	$\sigma=\sigma_{ss}>0$ (baseline institutional friction)

Interpretation:

1. **For equilibrium systems** (gases, isolated systems), the attractor is the state where entropy generation reaches zero — the system has nowhere lower to go.
2. **For dissipative systems** (cells, brains, societies), the attractor is the state where entropy generation reaches its lowest *non-zero* steady-state value — the minimum entropy generation the system can sustain while

maintaining its functional organization.

Important caveats:

- This is a proposed benchmark, not a derived theorem.
- For cognitive systems in particular, minimizing *entropy production rate* (a thermodynamic quantity) and minimizing *free energy/surprise* (the actual claim in the free-energy principle) are distinct minimization principles. The framework does not establish a bridge between them; this is an open question.
- The benchmark is an empirical hypothesis that requires domain-specific validation.

In all cases, the attractor is the **lowest entropy-generating state *that system can have* while remaining itself.**

---

7. Testable Predictions

7.1 Core Prediction

Prediction: The recovery rate κ is inversely proportional to the excess entropy generated during reconfiguration: $\kappa \propto \frac{1}{D_\infty}$

Falsification: If a system returns to its attractor with high excess entropy generation but high recovery rate, the prediction is falsified.

7.2 Secondary Prediction

Prediction: Systems that maintain their attractor with minimal excess entropy generation are more "efficient." Systems that generate excess entropy are "inefficient" or "stressed."

Falsification: If an inefficient system has lower excess entropy generation than an efficient system, the prediction is falsified.

7.3 Domain-Specific Predictions

Domain	Prediction	Falsification
Physical	κ correlates with thermal efficiency	κ high but efficiency low
Biological	κ correlates with metabolic efficiency	κ high but metabolic cost high
Cognitive	κ correlates with learning efficiency	κ high but learning cost high
Social	κ correlates with institutional efficiency	κ high but coordination cost high

---

8. Experimental Design

8.1 Physical Systems

- **System:** Gas in a piston
- **Perturbation:** Compression
- **Measurement:** Excess entropy generation (heat measurement) and recovery time
- **Test:** Correlation between κ and $1/D_\infty$

8.2 Biological Systems

- **System:** Cell culture
- **Perturbation:** Nutrient shock
- **Measurement:** Metabolic rate above resting (oxygen consumption) and recovery time

- **Test:** Correlation between κ and metabolic cost

8.3 Cognitive Systems

- **System:** Human participants in a learning task
- **Perturbation:** Prediction error
- **Measurement:** Free energy dissipation above baseline (EEG complexity, pupil dilation) and belief updating rate
- **Test:** Correlation between κ and free energy dissipation

8.4 Social Systems

- **System:** Institutional response to shocks
- **Perturbation:** Economic or political crisis
- **Measurement:** Social entropy production above baseline (allostatic load, cortisol, institutional friction) and recovery time
- **Test:** Correlation between κ and social entropy production

---

9. Open Questions

Question	Status	Difficulty
Q1: Uniqueness of $S(x)$	Are there multiple valid entropy functionals for a given domain?	Hard
Q2: Variational principle	Is there a universal variational principle that yields $S(x)$?	Hard
Q3: Social second law	Does $\sigma_{social} \geq 0$ always hold during recovery?	Very Hard

Question	Status	Difficulty
Q4: Cross-level entropy	How does entropy generation at one level relate to entropy generation at another?	Hard
Q5: Measurement	Can we measure excess entropy generation in cognitive and social systems directly?	Moderate
Q6: Unification	Can all domain-specific entropy functionals be derived from a single universal functional?	Very Hard

---

10. Conclusion

Every dissipative system maintains its attractor through continuous reconfiguration. Reconfiguration requires work; work generates excess entropy. The recovery rate κ — corrective permeability — is the rate at which a system reconfigures to return to its attractor after perturbation. We have proposed that κ is a measure of excess entropy generation rate.

We developed an abstract persistence cost framework and proved its equivalence to Lyapunov theory. We then identified entropy production as a physical realization of this cost, deriving: $\kappa = \inf_{x} \frac{\int_0^\infty \sigma_{excess}(\phi_t(x))\, dt}{\delta(x)}$

where $\sigma_{excess} = \sigma - \sigma_{ss}$ is the excess entropy production rate above the system's steady-state baseline — thermodynamic entropy for physical systems, metabolic entropy for biological systems, free energy dissipation for cognitive systems, and social entropy production for social systems.

We proposed a unified benchmark: the attractor is the state of minimum entropy generation for that class of system — zero for equilibrium systems, non-zero steady-state for dissipative systems. This provides a unified criterion for identifying attractors across domains: an attractor is a state from which the system cannot reduce its entropy generation further without losing its defining structure or function.

This unifies physical, biological, cognitive, and social systems. In each domain, persistence requires reconfiguration; reconfiguration generates excess entropy; κ measures the entropy cost of that reconfiguration. The framework is grounded in the second law of thermodynamics and non-equilibrium steady-state thermodynamics, not analogy.

Social Application: The framework provides a thermodynamic interpretation of social dynamics: harmony is a low-entropy attractor state; turbulence is a high-entropy state generated by excess dissipation during reconfiguration. The recovery rate κ measures how efficiently a society transitions from turbulence back to harmony — that is, how quickly it reduces its excess entropy production to zero.

---

11. Limitations

This paper establishes an abstract persistence cost framework with a proposed thermodynamic realization. Several limitations should be explicitly acknowledged:

1. **Uniqueness.** Entropy production is not proved to be the unique persistence cost. Many positive functionals $C(x)$ satisfy $\nabla D\cdot f=-C$. The identification of entropy production as the canonical cost is a physically motivated hypothesis, not a mathematical theorem.
2. **Scope.** The framework does not imply that all domains obey thermodynamics literally. The cognitive and social

realizations are proposed hypotheses requiring empirical validation.
3. **Decay assumption.** Exponential decay of σ_{excess} is a sufficient assumption to ensure finiteness of D_∞, not a necessary one. Generalization to L^1 integrable decays (e.g., algebraic) is a priority for future work.
4. **Basin depth.** Basin depth $B = D_\infty(\text{saddle})$ is defined in terms of the persistence cost functional. Its relationship to classical energy barriers is established only for gradient systems.
5. **Empirical validation.** The predictions of the framework — particularly the inverse relationship between κ and D_∞ — remain to be tested empirically across domains.
6. **Low-energy attractor benchmark.** The benchmark proposed in §6.3 is a hypothesis, not a derived theorem. For cognitive systems, it risks conflating thermodynamic entropy production with free-energy minimization — distinct principles whose relationship remains open.

References

Aubin, J. P. (1991). *Viability Theory*. Birkhäuser.

Boltzmann, L. (1877). “Über die Beziehung zwischen dem zweiten Hauptsatz der mechanischen Wärmetheorie und der Wahrscheinlichkeitsrechnung.” *Wiener Berichte*, 76, 373-435.

Clausius, R. (1865). “Über verschiedene für die Anwendung bequeme Formen der Hauptgleichungen der mechanischen Wärmetheorie.” *Annalen der Physik*, 125(7), 353-400.

Freeman, R. A., & Kokotovic, P. V. (1996). *Robust Nonlinear Control Design: State-Space and Lyapunov Techniques*.

Birkhäuser.

Freidlin, M. I., & Wentzell, A. D. (2012). *Random Perturbations of Dynamical Systems* (3rd ed.). Springer.

Friston, K. (2010). “The free-energy principle: a unified brain theory?” *Nature Reviews Neuroscience*, 11(2), 127-138.

Galida, R. (2026a). “The Persistence Functional: A Candidate Formal Foundation for the Attractor Framework.” *Fantasy Attractor*.

Galida, R. (2026b). “Deriving Corrective Permeability from the Cumulative Deviation Functional.” *Fantasy Attractor*.

Jaynes, E. T. (1957). “Information Theory and Statistical Mechanics.” *Physical Review*, 106(4), 620-630.

Khalil, H. K. (2002). *Nonlinear Systems* (3rd ed.). Prentice Hall.

Kondepudi, D., & Prigogine, I. (1998). *Modern Thermodynamics: From Heat Engines to Dissipative Structures*. Wiley.

Lohmiller, W., & Slotine, J. J. E. (1998). “On contraction analysis for non-linear systems.” *Automatica*, 34(6), 683-696.

Lyapunov, A. M. (1892). *The General Problem of the Stability of Motion*.

McEwen, B. S. (1998). “Stress, Adaptation, and Disease: Allostasis and Allostatic Load.” *Annals of the New York Academy of Sciences*, 840(1), 33-44.

Nicolis, G., & Prigogine, I. (1989). *Exploring Complexity: An Introduction*. W. H. Freeman.

Parrondo, J. M. R., Horowitz, J. M., & Sagawa, T. (2015). “Thermodynamics of information.” *Nature Physics*, 11(2), 131-139.

Prigogine, I. (1947). *Étude Thermodynamique des Phénomènes Irréversibles*. Dunod.

Prigogine, I., & Nicolis, G. (1977). *Self-Organization in Non-Equilibrium Systems*. Wiley.

Sagawa, T., & Ueda, M. (2008). "Second law of thermodynamics with discrete quantum feedback control." *Physical Review Letters*, 100(8), 080403.

Seifert, U. (2012). "Stochastic thermodynamics, fluctuation theorems and molecular machines." *Reports on Progress in Physics*, 75(12), 126001.

Sekimoto, K. (2010). *Stochastic Energetics*. Springer.

Shannon, C. E. (1948). "A Mathematical Theory of Communication." *Bell System Technical Journal*, 27(3), 379-423.

Sterling, P., & Eyer, J. (1988). "Allostasis: A New Paradigm to Explain Arousal Pathology." In *Handbook of Life Stress, Cognition and Health*, 629-649.

Suggested citation: Galida, R. S. (2026). Excess Entropy Production as a Candidate Universal Cost of Persistence: A Thermodynamic Foundation for the Attractor Framework. *Fantasy Attractor*.

Deriving Corrective Permeability from the

Cumulative Deviation Functional; Robert Galida (June 2026) [F]

Abstract

The attractor framework defines κ (corrective permeability) as the rate at which a system returns to its attractor after perturbation. Historically, κ has been treated as an empirical parameter — fitted to data rather than derived from first principles. This paper derives κ from the framework's foundational object: the cumulative deviation functional $D_T(x)=\int_0^T \delta(\phi_t(x))\,dt$, where $\delta(x)=d(x,\mathcal{A})$.

We define: $\kappa=\inf_{x\in B\setminus\mathcal{A}} \frac{\delta(x)}{D_\infty(x)}$

We prove that for linear systems $\dot{x}=-Ax$ with A symmetric positive definite, this definition recovers the slowest eigenvalue $\lambda_{\min}(A)$ — the conventional notion of corrective permeability. We establish a sharp universal persistence bound $D_\infty(x)\le\delta(x)/\kappa$, show homogeneity and scale invariance of the variational ratio, and demonstrate consistency with Koopman spectral theory and resolvent poles for finite-dimensional linear systems. A comparison theorem links κ to classical exponential stability constants. A Hamilton-Jacobi-type transport equation for D_∞ is derived. A finite-horizon estimator $\kappa_T=\inf_x \frac{\delta(x)}{D_T(x)}$ is provided with exponential convergence under explicit assumptions.

The derivation is rigorous for linear systems and testable. Open questions for nonlinear, multiscale, and stochastic systems are identified.

Keywords: corrective permeability, cumulative deviation functional, attractor framework, Koopman operator, trajectory functional

---

1. Introduction

The attractor framework has been applied across physics, biology, cognition, and social systems. Its central variable — corrective permeability κ — measures the rate at which a system returns to its attractor after perturbation. Historically, κ has been defined empirically as $\kappa=1/\tau$, where τ is a measured recovery time constant.

This paper derives κ from a single foundational object: the cumulative deviation functional $D_T(x)$. Within the present framework, κ is defined variationally rather than introduced as an empirical fitting parameter. We show that κ is a consequence of the trajectory geometry — specifically, the ratio of initial distance to total cumulative deviation.

The derivation is rigorous for linear systems, connects to established theory (Koopman operators, resolvent poles), and provides a finite-horizon estimator for empirical use. Open questions for nonlinear and stochastic systems are identified.

---

2. The Cumulative Deviation Functional

Let X be a metric space with distance function $\|\cdot-\cdot\|$. Let $\phi_t(x)$ be the flow of a dynamical system starting from state $x\in X$ at time $t=0$. Let $A\subseteq X$ be an attractor set (a compact, invariant set to which trajectories converge). Let B be the basin of attraction of A.

Define the distance from a point to the attractor: $$\delta(x) = d(x, A) = \inf_{a \in A} \|x - a\|$$

Definition 1 (Cumulative Deviation Functional): For a finite horizon $T > 0$, define: $$D_T(x) = \int_0^T \delta(\phi_t(x))\, dt$$

For $T \to \infty$, define: $$D_\infty(x) = \int_0^\infty \delta(\phi_t(x))\, dt$$

Proposition 1 (Finiteness of D_∞): Assume there exist constants $C < \infty$ and $\mu > 0$ such that: $$\delta(\phi_t(x)) \le C e^{-\mu t} \delta(x)$$

for all $x \in B$. Then $D_\infty(x) < \infty$ for every $x \in B$.

Proof: $$D_\infty(x) = \int_0^\infty \delta(\phi_t(x))\, dt \le \int_0^\infty C e^{-\mu t} \delta(x)\, dt = \frac{C}{\mu} \delta(x) < \infty \quad \square$$

Properties (from Galida, 2026a):

Property	Statement
Non-negativity	$D_T(x) \ge 0$
Monotonicity	$D_{T_2}(x) \ge D_{T_1}(x)$ for $T_2 \ge T_1$
Additivity	$D_{T+S}(x) = D_T(x) + D_S(\phi_T(x))$
Instantaneous growth	$\frac{d}{dT} D_T(x) = \delta(\phi_T(x))$
Occupation measure	$D_T(x) = \int \delta(y)\, d\mu_T(y)$, where μ_T is the occupation measure

---

3. Derivation of Corrective Permeability (κ)

3.1 Variational Definition

Definition 2 (Corrective Permeability): $$\kappa = \inf_{x \in B \setminus A} \frac{\delta(x)}{D_\infty(x)}$$

Interpretation: κ is the *effective* recovery rate — the smallest ratio of initial distance to total cumulative deviation. It serves as a global measure of the slowest recovery mode in the basin.

Remark on κ: The definition allows $\kappa = 0$ if $D_\infty(x)$ diverges or if the ratio $\delta(x)/D_\infty(x)$ can be made arbitrarily small. Throughout the remainder of this paper, we assume hypotheses (such as the exponential stability in Proposition 1) that guarantee $\kappa > 0$.

Remark on attainment: The infimum in the definition of κ need not be attained; minimizing sequences may exist without a minimizing state. For linear systems, the infimum is attained on the slow eigenspace.

3.2 Homogeneity and Scale Invariance

Theorem 1 (Homogeneity and Scale Invariance): Suppose the flow satisfies $\phi_t(\alpha x) = \alpha \phi_t(x)$ for all t and all $\alpha > 0$, and the distance function satisfies $\delta(\alpha x) = \alpha \delta(x)$. Then: $$\frac{\delta(\alpha x)}{D_\infty(\alpha x)} = \frac{\delta(x)}{D_\infty(x)}$$

Proof: $$D_\infty(\alpha x) = \int_0^\infty \delta(\phi_t(\alpha x))\, dt = \int_0^\infty \delta(\alpha \phi_t(x))\, dt = \alpha \int_0^\infty \delta(\phi_t(x))\, dt = \alpha D_\infty(x)$$

Corollary: For linear systems, the infimum over all $x \neq 0$ reduces to an infimum over the unit sphere:
$$\kappa = \inf_{\|x\|=1} \frac{\delta(x)}{D_\infty(x)}$$

3.3 Sharp Universal Persistence Bound

Theorem 2 (Sharp Universal Persistence Bound): For any $x \in \mathcal{B}\setminus\mathcal{A}$:
$$D_\infty(x) \leq \frac{\delta(x)}{\kappa}$$

Moreover, the constant $1/\kappa$ is optimal: it is the *smallest* constant such that this inequality holds for all x in the basin.

Proof: By definition of κ as the infimum of $\delta(x)/D_\infty(x)$, we have $\delta(x)/D_\infty(x) \geq \kappa$ for all x. Rearranging gives:
$$D_\infty(x) \leq \frac{\delta(x)}{\kappa}$$

Optimality follows from Theorem 3: for the slow eigenvector v_1, $D_\infty(v_1) = \delta(v_1)/\kappa$, so no smaller constant can work. $\square$

3.4 Consistency with Linear Systems

Consider a linear system $\dot{x} = -Ax$, with A symmetric positive definite. Let its eigenvalues be $0 < \lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$, with corresponding orthonormal eigenvectors $v_1, v_2, \ldots, v_n$.

The flow is $\phi_t(x) = e^{-At}x$. The attractor is $\mathcal{A} = \{0\}$, and the distance to the attractor is $\delta(x) = \|x\|$.

Theorem 3 (Linear Consistency): For $\dot{x} = -Ax$ with A symmetric positive definite, $\inf_{x \neq 0} \frac{D_\infty(x)}{\|x\|} = \lambda_{\min}(A)$

Proof:

Since A is symmetric positive definite, e^{-At} is symmetric positive definite with eigenvalues $e^{-\lambda_i t}$. Hence its operator norm is $\|e^{-At}\| = e^{-\lambda_1 t}$. For any $x \neq 0$: $D_\infty(x) = \int_0^\infty \|e^{-At}x\|\,dt \leq \int_0^\infty \|x\| e^{-\lambda_1 t}\,dt = \frac{\|x\|}{\lambda_1}$

Therefore: $\frac{D_\infty(x)}{\|x\|} \geq \lambda_1$

To show equality is achieved, take $x = v_1$ (the eigenvector corresponding to λ_1). Then: $\|e^{-At}v_1\| = \|v_1\| e^{-\lambda_1 t}$

and: $D_\infty(v_1) = \int_0^\infty \|v_1\| e^{-\lambda_1 t}\,dt = \frac{\|v_1\|}{\lambda_1}$

Thus: $\frac{D_\infty(v_1)}{\|v_1\|} = \lambda_1$

Hence: $\inf_{x \neq 0} \frac{D_\infty(x)}{\|x\|} = \lambda_1$ □

Corollary: For linear systems, the variational definition of κ recovers the slowest eigenvalue — the conventional notion of corrective permeability.

3.5 Transport Equation

Theorem 4 (Transport Equation): Assume the vector field f is C^1, the flow ϕ_t is C^1, and D_∞ is continuously differentiable on $B(A)$. Then: $\nabla D_\infty(x) \cdot f(x) = -\delta(x)$

Proof: From the definition: $D_\infty(\phi_s(x)) = D_\infty(x) - D_s(x)$

Differentiating with respect

to s at $s=0$: $\frac{d}{ds} D_\infty(\phi_s(x))\Big|_{s=0} = -\delta(x)$

By the chain rule: $\nabla D_\infty(x) \cdot f(x) = -\delta(x)$ $\square$

Interpretation: This is a first-order transport equation, $f \cdot \nabla D = -\delta$, which belongs to the broader Hamilton-Jacobi family but lacks a Hamiltonian in the usual sense. It may serve as a foundation for numerical computation and further theoretical development.

3.6 Local vs. Global Interpretation

The variational definition $\kappa = \inf_x \frac{\delta(x)}{D_\infty(x)}$ is **global** — it is the slowest recovery rate over the entire basin. This is not necessarily the same as the local recovery rate near the attractor (the slowest eigenvalue of the linearization). For linear systems, they coincide. For nonlinear systems, they may differ if transient excursions produce slower effective recovery than the local linearization predicts.

This distinction is important: κ is a global invariant of the basin, not merely a local property of the attractor. The relationship between the global κ and the local Lyapunov exponent is an open question (see §6).

3.7 Non-Symmetric Linear Systems

For a general linear system $\dot{x} = Ax$ (where A is stable, i.e., all eigenvalues have negative real parts), the same principle holds in the diagonalizable case. The slowest mode corresponds to the eigenvalue with the largest real part (closest to zero).

Conjecture: An analogous result holds for non-normal linear systems under additional assumptions on the semigroup, such as a uniformly exponentially stable semigroup satisfying suitable norm bounds. This remains an open question.

3.8 Comparison with Exponential Stability

Theorem 5 (Comparison with Exponential Stability): Suppose the system satisfies the exponential stability bound:$$\delta(\phi_t(x)) \le C e^{-\mu t}\delta(x)$$

for all $x \in B$, with constants $C < \infty$ and $\mu > 0$. Then:$$\kappa \ge \frac{\mu}{C}$$

Proof: From the stability bound:$$D_\infty(x) = \int_0^\infty \delta(\phi_t(x))\,dt \le \int_0^\infty C e^{-\mu t}\delta(x)\,dt = \frac{C}{\mu}\delta(x)$$

Therefore:$$\frac{\delta(x)}{D_\infty(x)} \ge \frac{\mu}{C}$$

Taking the infimum over x:$$\kappa = \inf_x \frac{\delta(x)}{D_\infty(x)} \ge \frac{\mu}{C} \quad \square$$

Interpretation: The variational constant κ is bounded below by the exponential stability constant μ/C.

---

4. Connections to Existing Theory

4.1 Koopman Operator

The Koopman operator K_t acts on observables as:$$(K_t f)(x) = f(\phi_t(x))$$

For linear systems $\dot{x} = -Ax$, the Koopman eigenvalues are $e^{-\lambda_i t}$. The dominant nontrivial eigenvalue (largest less than 1) is $e^{-\lambda_1 t}$, corresponding to the slowest decay rate.

For finite-dimensional linear systems, $\rho = e^{-\lambda_{\min} t}$, and therefore:

$$-\frac{1}{t}\log\rho = \lambda_{\min} = \kappa$$

Thus, under the hypotheses of Theorem 3, the variational constant equals the exponential decay rate associated with the dominant Koopman eigenvalue.

4.2 Resolvent Poles

For finite-dimensional stable linear systems, the resolvent $(sI+A)^{-1}$ has poles at $s = -\lambda_i$. The pole closest to the imaginary axis is $s = -\lambda_1$.

Since Theorem 3 identifies $\kappa = \lambda_{\min}$, and the resolvent poles are $s_i = -\lambda_i$, we obtain:

$$\kappa = \min_i |\Re(s_i)|$$

for finite-dimensional linear systems.

---

5. Finite-Horizon Estimation

In practice, we can only measure finite trajectories. Define the finite-horizon estimator:

$$\kappa_T = \inf_{x \in K} \frac{\delta(x)}{D_T(x)}$$

where $K \subset B$ is compact and $K \cap A = \emptyset$.

Proposition 2 (Finite-Horizon Estimation): Assume:

1. The flow $\phi_t(x)$ is jointly continuous

in (t,x).
2. $\delta(x)$ is continuous.
3. The exponential stability bound $\delta(\phi_t(x)) \le Ce^{-\mu t}\delta(x)$ holds uniformly for all $x \in K$, with $\mu > 0$.

Then the variational constant κ (from Definition 2) satisfies $\kappa \ge \mu/C$ by Theorem 5, and:$\kappa_T \to \kappa$ as $T \to \infty$

with error:$|\kappa_T - \kappa| = O(e^{-\mu T})$

Proof: For any $x \in K$, the tail bound gives:$|D_\infty(x) - D_T(x)| = \int_T^\infty \delta(\phi_t(x))\,dt \le \frac{C e^{-\mu T}\delta(x)}{\mu}$

Since $\delta(x)$ is bounded on the compact set K, let $M = \sup_{x \in K} \delta(x) < \infty$. Then:$|D_\infty(x) - D_T(x)| \le \frac{CMe^{-\mu T}}{\mu}$

The right-hand side is independent of x and tends to zero as $T \to \infty$. Hence $D_T \to D_\infty$ uniformly on K.

Moreover, since K is compact and $K \cap A = \varnothing$, continuity of δ gives $\inf_{x \in K} \delta(x) > 0$. Since $D_T(x)$ is continuous (by assumptions 1–2) and monotonically non-decreasing in T (from §2), for any fixed finite $T_0 > 0$, $D_\infty(x) \ge D_{T_0}(x)$, and D_{T_0} is continuous and strictly positive on K. A continuous, strictly positive function on a compact set has a positive infimum:$m = \inf_{x \in K} D_{T_0}(x) > 0$

Thus:$\inf_{x \in K} D_\infty(x) \ge m > 0$

Uniform convergence of D_T to D_∞ on K therefore implies uniform convergence of $\delta(x)/D_T(x)$ to $\delta(x)/D_\infty(x)$. Consequently, the infima converge.$\square$

6. Open Questions

Question	Status	Difficulty
Q1: Nonlinear systems	Does $\inf \frac{\delta}{D_\infty}$ equal the local Lyapunov exponent?	Hard
Q2: Local vs. global consistency	Does $\lim_{x \to A} \frac{\delta(x)}{D_\infty(x)} = \kappa$ hold for general nonlinear systems?	Hard
Q3: Non-normal systems	Does the infimum equal the slowest eigenvalue for non-normal A?	Moderate
Q4: Multiple timescales	Does the infimum isolate the slowest timescale?	Hard
Q5: Stochastic systems	How does noise affect the finite-horizon estimator?	Hard
Q6: Multiple attractors	How does κ behave in basins with multiple attractors?	Moderate

7. Conclusion

This paper derives corrective permeability κ from the cumulative deviation functional $D_T(x)$. The variational definition: $\kappa = \inf_x \frac{\delta(x)}{D_\infty(x)}$

is shown to recover the slowest eigenvalue for linear systems, consistent with the conventional empirical definition $\kappa = 1/\tau$. A sharp universal persistence bound $D_\infty(x) \le \delta(x)/\kappa$ is established. A comparison theorem links κ to classical exponential stability constants. A Hamilton-Jacobi-type transport equation for D_∞ is derived. Connections to Koopman theory and resolvent theory are established for finite-dimensional linear systems. A finite-horizon estimator κTκT is provided with exponential convergence under explicit assumptions.

Key contribution: Within the present framework, κκ is defined variationally rather than introduced as an empirical fitting parameter — at least for the class of systems analyzed here.

Next steps: Extend the derivation to nonlinear systems (Q1–Q2), non-normal systems (Q3), multiple timescales (Q4), and stochastic dynamics (Q5).

References

Crandall, M. G., Ishii, H., & Lions, P. L. (1992). “User’s Guide to Viscosity Solutions of Second Order Partial Differential Equations.” *Bulletin of the American Mathematical Society*, 27(1), 1-67.

Evans, L. C. (2010). *Partial Differential Equations*. American Mathematical Society.

Galida, R. (2026a). “The Persistence Functional: A Candidate Formal Foundation for the Attractor Framework.” *Fantasy Attractor*.

Hale, J. K. (1988). *Asymptotic Behavior of Dissipative Systems*. American Mathematical Society.

Hirsch, M. W., Smale, S., & Devaney, R. L. (2004). *Differential Equations, Dynamical Systems, and an Introduction to Chaos* (2nd ed.). Elsevier Academic Press.

Khalil, H. K. (2002). *Nonlinear Systems* (3rd ed.). Prentice Hall.

Koopman, B. O. (1931). “Hamiltonian Systems and Transformations in Hilbert Space.” *Proceedings of the National Academy of Sciences*, 17(5), 315-318.

Lyapunov, A. M. (1892). *The General Problem of the Stability of Motion*. (English translation: 1992, Taylor & Francis).

Mezić, I. (2005). “Spectral Properties of Dynamical Systems, Model Reduction and Decompositions.” *Nonlinear Dynamics*, 41(1-3), 309-325.

Pazy, A. (1983). *Semigroups of Linear Operators and Applications to Partial Differential Equations*. Springer.

Vidyasagar, M. (1993). *Nonlinear Systems Analysis* (2nd ed.). Prentice Hall.

Suggested citation: Galida, R. S. (2026). Deriving Corrective Permeability from the Cumulative Deviation Functional. *Fantasy Attractor*.

The Persistence Functional: A Candidate Formal Foundation for the Attractor Framework; Robert Galida (July 2026) [F]

Abstract

The attractor framework provides a domain-general vocabulary for describing persistence and change across physical, biological, cognitive, and social systems. However, its core variables—κ (corrective permeability), B (basin depth), and R (reality alignment)—have been defined inconsistently across application papers, and their formal relationships have remained implicit. This paper proposes a candidate mathematical formalization for the framework.

The central mathematical innovation of this paper is treating persistence as a functional defined over trajectories—$D_T(x)=\int_0^T d(\phi_\tau(x),\mathrm{A})\,d\tau$—rather than as a scalar property of states. We prove several mathematical properties of D_T, including non-negativity, monotonicity in T, additivity, Lipschitz continuity with respect to initial conditions, and a bound relating D_∞ to the recovery rate κ: $D_\infty(x)\leq\frac{C}{\kappa}d(x,\mathrm{A})$. We establish connections to dynamic programming and ergodic theory via occupation measures. We introduce a complementary **topological persistence functional** $P_{\text{topo}}(t)$, which measures the lifetime of topological features in the trajectory's state-space geometry, and the **topological evolution rate** $E(t)$.

We unify the framework's variable set: κ is the recovery rate (operationalized as $1/\tau$); γ is a proposed drift rate for persistent chaos, grounded in the literature on high-dimensional neural networks; B is the energy barrier (basin depth); $\tilde{B}$ is a complementary persistence depth; R is the expected log predictive likelihood. We propose testable predictions linking $E(t)$ to κ and γ, and provide a falsifiable experimental protocol using neural network training and persistent homology.

The paper offers a candidate formal foundation, with explicit

definitions, mathematical properties, and empirical grounding. All unverified sources are clearly labeled as such.

Keywords: attractor framework, persistence functional, cumulative deviation, topological persistence, corrective permeability, basin depth, reality alignment, persistent homology

---

1. Introduction

The attractor framework has been applied across physics (hydrogen decay, Jeans instability), biology (ECM mechanics, HRV), cognition (belief updating, performance attractors), and social systems (religious attractors, civilizational dynamics). A common vocabulary has emerged: κ (corrective permeability), B (basin depth), and R (reality alignment). However, these variables have been defined inconsistently across papers, and their formal relationships have remained implicit. This paper proposes a candidate mathematical formalization that addresses these inconsistencies.

The central mathematical innovation of this paper is treating persistence as a functional defined over trajectories rather than as a scalar property of states. $D_T(x)=\int_0^T d(\phi_\tau(x),A)\,d\tau$ can be understood as a type of **action functional** (carefully qualified). Like the classical action $\int L(q,\dot{q})\,dt$, it assigns a scalar to an entire trajectory, is additive under concatenation, and suggests variational and optimal-control interpretations. However, it is not the mechanical action; it is a cumulative deviation functional that measures time away from equilibrium. This moves the framework into the domain of trajectory-level analysis, aligning it with modern dynamical systems and geometric control theory.

We introduce the **cumulative deviation functional** $D_T(x)$ as this central object, and we establish its mathematical properties, including its relationship to the recovery rate κ. We introduce a complementary **topological persistence functional** $P_{\text{topo}}(t)$ and the **topological evolution rate** $E(t)$. We unify the framework's variable set with operational definitions and propose testable predictions with falsification criteria.

1.1 Scope and Status

This paper is a **candidate formalization**—it provides definitions, mathematical properties, and empirical hypotheses. It is not a completed empirical validation; that is the subject of future work. All claims are labeled as **definitions** (part of the formal structure), **propositions/theorems** (proved), **hypotheses** (testable predictions), or **heuristics** (suggestive connections not yet formalized). This distinction is maintained throughout.

---

2. Formal Definitions

Let X be a metric space with distance function $\|\cdot - \cdot\|$. Let $\phi_\tau(x)$ be the flow of a dynamical system starting from state $x \in X$ at time $\tau = 0$. Let $A \subseteq X$ be an attractor set (a compact, invariant set to which trajectories converge). Assume the flow is continuous and measurable so that $d(\phi_\tau(x), A)$ is measurable. The flow ϕ_τ satisfies the semigroup property $\phi_{t+s} = \phi_t \circ \phi_s$ for all $t, s \geq 0$, with $\phi_0 = \text{id}$. We assume $d(\phi_\tau(x), A) \in L^1([0, T])$ for all finite T, so the integral defining D_T is well-defined.

Define the distance from a point to the attractor: $d(x, A) = \inf_{a \in A} \|x - a\|$

The definition applies to any metric space; for infinite-dimensional spaces, the usual measurability and integrability conditions are assumed.

2.1 Cumulative Deviation Functional

Definition 1 (Cumulative Deviation Functional): For a finite horizon $T>0$, the cumulative deviation functional is:$$D_T(x)=\int_0^T d(\phi_\tau(x),A)\,d\tau$$

Interpretation: $D_T(x)$ is the total accumulated deviation from the attractor over the interval $[0,T]$. It measures integrated error, residence-time-weighted distance, or accumulated regret. This is **not** a path length; it measures time spent away from equilibrium, whereas path length $\int\|\dot{\phi}_\tau(x)\|\,d\tau$ measures distance traveled.

Domain generality: This definition applies to any system with a well-defined state space, a flow, and an attractor set. It does not require linearity, differentiability, or specific functional forms.

Empirical note: D_T is the fundamental object for empirical work; D_∞ is primarily an analytical limit used for theoretical bounds.

Note: D_T is not a Lyapunov function. A Lyapunov function is a scalar function of the current state; D_T is a functional of the entire trajectory. It does not decrease monotonically along trajectories, and it does not provide pointwise stability information. Its purpose is to measure accumulated history, not instantaneous energy.

Occupation measure connection: Define the occupation measure of the trajectory up to time T as:$$\mu_T(B)=\int_0^T \mathbf{1}_B(\phi_\tau(x))\,d\tau$$

for measurable $B\subseteq X$. Then:$$D_T(x)=\int_X d(y,A)\,d\mu_T(y)$$

Thus D_T is the expected distance to the attractor under the occupation measure. This connects the functional directly to ergodic theory and occupation measure analysis. For foundational treatments of occupation measures and invariant measures, see Ruelle (1989) and Bowen (1975).

2.1.1 Why the L¹ Trajectory Functional?

The choice of the L¹ integral over alternatives is motivated by the following properties:

- **Linearity:** Each moment contributes equally; accumulation is additive over time.
- **Physical units:** For systems with a natural distance metric, D_T has units of distance × time, which is interpretable as accumulated deviation.
- **Simplicity:** It is the simplest nontrivial trajectory functional that is not a path length.
- **Analogy:** It mirrors cumulative regret and occupation measures in control theory and ergodic theory.
- **Avoidance of overweighting:** Unlike d^2, it does not disproportionately weight large deviations; unlike max, it is sensitive to the full trajectory.

This is one natural choice; other functionals (e.g., d^p, exponentially weighted integrals) could be substituted without changing the framework's structure.

2.2 Topological Persistence Functional

Let $X_\tau = \{\phi_s(x) : s \in [0,\tau]\}$ be the trajectory segment up to time τ. Let $PH_k(X_\tau)$ be the k-dimensional persistent homology of the point cloud X_τ at scale ϵ. Each feature (component, loop, void) has a birth scale b and a death scale d, with persistence $d-b$. For foundational treatments of persistent homology, see Edelsbrunner & Harer (2010) or Carlsson (2009).

Definition 2 (Topological Persistence Functional): We define the following complementary topological persistence functional.
For $t \geq 0$: $P_{topo}(t) = \int_0^t \sum_{k \geq 0} \sum_{(b,d) \in PH_k(X_\tau)} (d-b)\, d\tau$

The map $\tau \mapsto PH_k(X_\tau)$ is piecewise constant on intervals where the trajectory does not cross a homology-critical threshold. Assuming the trajectory crosses such thresholds at discrete times, the integral is well-defined as a sum of piecewise continuous segments. This is the standard assumption in time-varying persistent homology (see Carlsson & Zomorodian, 2009).

Interpretation: $P_{topo}(t)$ is the total lifetime of all topological features in the trajectory's state-space geometry up to time t. This is a separate mathematical object from DT; the relationship between them is an empirical hypothesis. This is one possible choice among several topological summaries (e.g., persistence landscapes, persistence images) and is selected because it mirrors the cumulative interpretation of DT, rather than because it is uniquely canonical. Other stable summaries—such as persistence landscapes, persistence images, or Betti curves—could be substituted for the present functional without changing the framework's structure.

Measurement: In practice, $P_{topo}(t)$ is computed by sampling the trajectory at discrete times, computing persistent homology on latent activation manifolds, and summing the persistence of all features using standard libraries (e.g., GUDHI, Ripser). Turner & Barak (2023) demonstrated that trained RNNs develop attractors sequentially during training; the topological structure of these attractors can be analyzed using persistent homology.

Falsification: If persistent homology features do not correlate with any behavioral or dynamical measure in a given system, P_{topo} is not a useful construct for that domain.

2.3 Topological Evolution Rate

Definition 3 (Topological Evolution Rate): For a learning system with time-dependent topological persistence, the topological evolution rate is defined as: $E(t) = \frac{d}{dt} P_{\text{topo}}(t)$

where differentiable, and experimentally as $E(t) \approx \frac{\Delta P_{\text{topo}}}{\Delta t}$ over finite intervals.

Interpretation: $E(t)$ measures how quickly the system's topological complexity changes during learning. Negative $E(t)$ indicates topological simplification (compression); positive $E(t)$ indicates increasing complexity (expansion); $E(t) \approx 0$ indicates stagnation. Learning is one possible cause of topological change; random drift, noise, or chaotic wandering can also change topology.

Empirical anchor: Karuppiah, Nazreen Banu et al. (2026) examine the evolution of topological signatures during training. Turner & Barak (2023) show that RNNs develop attractors sequentially, which may correspond to phases of topological simplification. We hypothesize that successful learning corresponds to negative average values of $E(t)$ over defined phases, but this is a testable claim, not a definition.

---

3. Mathematical Properties of the Cumulative Deviation Functional

This section establishes the mathematical behavior of D_T, providing the foundation for its use in the framework.

3.1 Non-negativity

Proposition 1 (Non-negativity): For any $x \in X$ and any $T \geq 0$: $$D_T(x) \geq 0$$

with equality iff $\phi_\tau(x) \in A$ for almost all $\tau \in [0, T]$.

Proof: The integrand is a distance function $d(\phi_\tau(x), A)$, which is non-negative by definition. The integral of a non-negative function is non-negative. Equality holds only if the integrand is zero almost everywhere.

3.2 Monotonicity in T

Proposition 2 (Monotonicity): For fixed x, $D_T(x)$ is monotonically non-decreasing in T: $$D_{T_2}(x) \geq D_{T_1}(x) \quad \text{for } T_2 \geq T_1$$

Proof: For $T_2 \geq T_1$: $$D_{T_2}(x) = \int_0^{T_1} d(\phi_\tau(x), A)\, d\tau + \int_{T_1}^{T_2} d(\phi_\tau(x), A)\, d\tau$$

The second integral is non-negative by Proposition 1. Therefore $D_{T_2}(x) \geq D_{T_1}(x)$.

Corollary: If the trajectory converges exactly to the attractor at time $\tau_0 < T$, then: $$D_T(x) = D_{\tau_0}(x) \quad \text{for all } T \geq \tau_0$$

3.3 Additivity

Proposition 3 (Additivity): For any $T, S \geq 0$: $D_{T+S}(x) = D_T(x) + D_S(\phi_T(x))$

Proof: $D_{T+S}(x) = \int_0^{T+S} d(\phi_\tau(x), A)\, d\tau = \int_0^T d(\phi_\tau(x), A)\, d\tau + \int_T^{T+S} d(\phi_\tau(x), A)\, d\tau = D_T(x) + \int_0^S d(\phi_{\tau+T}(x), A)\, d\tau = D_T(x) + \int_0^S d(\phi_\tau(\phi_T(x)), A)\, d\tau$ (by the semigroup property) $= D_T(x) + D_S(\phi_T(x))$ □

This connects D_T naturally to Bellman equations, dynamic programming, and occupation measures.

3.4 Heuristic Connection: Dynamic Programming

The additivity property $D_{T+S}(x) = D_T(x) + D_S(\phi_T(x))$ suggests a natural connection to dynamic programming. For a controlled system $\dot{X} = f(X, u)$ with control $u \in U$, the value function $V(x) = \inf_u D_\infty(x)$ would formally satisfy the Hamilton-Jacobi-Bellman equation: $0 = \inf_u \{d(x, A) + \nabla V(x) \cdot f(x, u)\}$

This is a standard result for additive cost functionals. A full derivation for the specific functional D_T is left for future work. This section is a heuristic connection, not a formal result.

3.5 Lipschitz Continuity with Respect to Initial Conditions

Proposition 4 (Lipschitz Continuity of D_T): Suppose the flow ϕ_τ is Lipschitz continuous in x with constant L, i.e., $\|\phi_\tau(x)-\phi_\tau(y)\| \le e^{L\tau}\|x-y\|$. Then for any x,y in the basin of A: $|D_T(x)-D_T(y)| \le \int_0^T e^{L\tau}\,d\tau\,\|x-y\| = \frac{e^{LT}-1}{L}\|x-y\|$

Proof: First, note that the distance function $d(\cdot,A)$ is 1-Lipschitz: for any $x,y \in X$, $|d(x,A)-d(y,A)| \le \|x-y\|$

This follows from the triangle inequality and the definition of the infimum. Then, using the Lipschitz property of the flow: $|D_T(x)-D_T(y)| \le \int_0^T |d(\phi_\tau(x),A)-d(\phi_\tau(y),A)|\,d\tau \le \int_0^T \|\phi_\tau(x)-\phi_\tau(y)\|\,d\tau \le \int_0^T e^{L\tau}\|x-y\|\,d\tau = \frac{e^{LT}-1}{L}\|x-y\|$

Interpretation: This proposition guarantees that empirical estimates of D_T are robust under small perturbations of initial conditions and establishes that D_T defines a continuous functional on the basin of attraction. This is essential for numerical estimation and experimental measurement.

3.6 Instantaneous Growth Rate

Remark 1 (Instantaneous Growth Rate): If the integrand $d(\phi_\tau(x),A)$ is continuous in τ, then: $\frac{d}{dT}D_T(x) = d(\phi_T(x),A)$

This follows directly from the Fundamental Theorem of Calculus.

3.7 Ergodic Limit

Proposition 5 (Ergodic Limit): Suppose the normalized occupation measure $\nu_T=\mu_T/T$ converges weakly to an invariant probability measure μ as $T\to\infty$. Then: $$\lim_{T\to\infty}\frac{1}{T}D_T(x)=\int_X d(y,A)\,d\mu(y)$$

Proof: From the occupation measure representation $D_T(x)=\int d(y,A)\,d\mu_T(y)=T\int d(y,A)\,d\nu_T(y)$, weak convergence of ν_T to μ and boundedness/continuity of $d(\cdot,A)$ gives the result.

This is the pointwise ergodic theorem applied to the observable $d(\cdot,A)$. For the ergodic theory of dynamical systems, see Bowen (1975) and Ruelle (1989).

3.8 Bound under Exponential Stability

Theorem 2 (Bound under Exponential Stability): Suppose the flow $\phi_\tau(x)$ converges to the attractor A with exponential rate $\kappa>0$: $$d(\phi_\tau(x),A)\le Ce^{-\kappa\tau}d(x,A)$$

for some constant $C<\infty$, for all $\tau\ge 0$. Then: $$D_\infty(x)=\int_0^\infty d(\phi_\tau(x),A)\,d\tau\le\frac{C}{\kappa}d(x,A)$$

Proof: $$D_\infty(x)=\int_0^\infty d(\phi_\tau(x),A)\,d\tau\le\int_0^\infty Ce^{-\kappa\tau}d(x,A)\,d\tau$$

$Ce^{-\kappa\tau}d(x,A)\,d\tau = Cd(x,A)\int_0^\infty e^{-\kappa\tau}\,d\tau = \frac{C}{\kappa}d(x,A)$

Corollary: For linearly stable systems with recovery rate κ, $D_\infty(x) \le \frac{1}{\kappa}d(x,A)$ (when $C=1$).

Important: Exponential stability implies $D_\infty < \infty$. The converse is not claimed; polynomial convergence can also yield finite D_∞.

3.9 Recovery Rate Bound

Corollary 1 (Recovery Rate Bound): For a system satisfying the exponential stability hypothesis with constant C, the recovery rate κ satisfies: $\kappa \le \frac{C\, d(x,A)}{D_\infty(x)}$

For systems with $C=1$ (e.g., normal/symmetric linearizations with no transient overshoot), this reduces to: $\kappa \le \frac{d(x,A)}{D_\infty(x)}$

Proof: From Theorem 2, we have $D_\infty(x) \le \frac{C}{\kappa}d(x,A)$. Rearranging gives $\kappa \le \frac{C\, d(x,A)}{D_\infty(x)}$. When $C=1$, this reduces to $\kappa \le \frac{d(x,A)}{D_\infty(x)}$.

Interpretation: Small cumulative deviation implies rapid recovery (large κ). Large cumulative deviation implies slow recovery (small κ). This formalizes the intuitive link between D_T and κ. The C factor accounts for possible transient overshoot in non-normal systems.

3.10 Finite Horizon Approximation

Proposition 6 (Finite Horizon): For any $\epsilon > 0$, there exists a finite T_ϵ such that for all $T > T_\epsilon$: $|D_T(x) - D_\infty(x)| \le \epsilon$

$(x) - D_\infty(x)| \leq \epsilon$

Proof: This follows directly from Theorem 2 under the exponential stability hypothesis. Since the integrand decays exponentially, the tail integral $\int_T^\infty d(\phi_\tau(x), A)\, d\tau$ can be made arbitrarily small by choosing T sufficiently large.

3.11 Summary of Properties

Property	Statement
Non-negativity	$D_T(x) \geq 0$
Monotonicity	$D_{T_2}(x) \geq D_{T_1}(x)$ for $T_2 \geq T_1$
Additivity	$D_{T+S}(x) = D_T(x) + D_S(\phi_T(x))$
Lipschitz continuity	$\lvert D_T(x) - D_T(y) \rvert \leq \frac{e^{LT} - 1}{L} \lvert x - y \rvert$
Instantaneous growth	$\frac{d}{dT} D_T(x) = d(\phi_T(x), A)$
Ergodic limit	$\lim_{T\to\infty} \frac{1}{T} D_T(x) = \int d(y, A)\, d\mu(y)$
Exponential stability implies finite D_∞	$D_\infty(x) \leq \frac{C}{\kappa} d(x, A)$
Recovery bound (general)	$\kappa \leq \frac{C\, d(x, A)}{D_\infty(x)}$
Recovery bound (C=1)	$\kappa \leq \frac{d(x, A)}{D_\infty(x)}$
Finite horizon approximation	$D_T(x) \to D_\infty(x)$ as $T \to \infty$

4. The Unified Variable Set

The following variables are defined operationally. Where a variable is a proposal, that is stated explicitly.

4.1 Corrective Permeability (κ)

Definition 4 (Corrective Permeability): κ is the recovery rate of the system to its attractor after a small perturbation. Operationally estimated as $\kappa = 1/\tau$ under approximately exponential relaxation, where τ is the characteristic recovery time constant. This coincides with the exponential convergence exponent in the linearized regime and is consistent with the original definition in the attractor framework.

Relationship to DT: From Corollary 1, for a system with initial deviation $d(x, A)$, $\kappa \le \frac{D_\infty(x)}{C\, d(x, A)}$.

Note on κ's status: In this paper, κ is treated as a primitive empirical regime parameter. A stronger theory would derive κ from DT and system geometry; this remains an open direction for future work.

4.2 Drift Rate (γ) — A Proposed Distinction

Definition 5 (Drift Rate): We propose the following operational distinction between dynamical regimes, based on the dominant Lyapunov exponent $\lambda_{\max}$:

Regime	λ_{max}	κ	γ	Behavior
Stable attractor	<-0.01	>0	0	Converges to fixed point
Persistent chaos	≈ 0	≈ 0	>0	Wanders without convergence
Full chaos	>0	undefined	>0	Diverges

Thresholds: $\lambda_{max} < -0.01$, $|\lambda_{max}| \leq 0.01$, and $\lambda_{max} > 0.01$ (pre-registered, measured in units of 1/epoch). These numerical thresholds are illustrative defaults rather than theoretically privileged constants.

Grounding: This distinction is inspired by the literature on chaos in high-dimensional neural networks (Engelken, Wolf & Abbott, 2023; Sompolinsky, Crisanti & Sommers, 1988; Clark, Abbott & Litwin-Kumar, 2023; Fournier & Urbani, 2023). For the treatment of stochastic and random perturbations, see Arnold (1998).

Falsification: If κ and γ are perfectly correlated (i.e., systems with small κ always have small γ), the distinction is not useful.

4.3 Basin Depth (B) and Persistence Depth ($\tilde{B}$)

Definition 6a (Basin Depth — Energy Barrier): B is the energy barrier required to escape the basin, measured as the potential difference between the attractor and the saddle point on the basin boundary:

$$B = V(\text{saddle}) - V(\text{attractor})$$

This preserves the original definition from earlier papers.

Definition 6b (Persistence Depth): As a complementary measure, we define:

$$\tilde{B} = \min_{x \in \partial B} DT(x)$$

This is the cumulative deviation required to reach the basin boundary. The relationship between B and $\tilde{B}$ remains an open mathematical question.

Operational alternative: In practice, the basin boundary may not be well-defined. Estimate B via the Arrhenius relationship $P_{\text{escape}} \propto e^{-B/T}$, where T is the noise level.

4.4 Reality Alignment (R)

Definition 7 (Reality Alignment): R is the expected log predictive likelihood: $R = \mathbb{E}[\log p(y \mid X)]$

where $p(y \mid X)$ is the system’s predictive distribution over outcomes y given state X. Higher R indicates better predictive accuracy. This is a standard measure of predictive performance; the label “reality alignment” is a philosophical interpretation.

Direction-dependence: The framework interprets R as potentially direction-dependent: $R_{A\to B} \neq R_{B\to A}$. This captures the asymmetry found in Berglund et al. (2024), where models trained on “A is B” fail to generalize to “B is A.” This interpretation is a framework-level claim.

Note on integration: Among the core variables, R is the least integrated with the trajectory-based formalism. Unlike κ, B, and $\tilde{B}$, which are directly derived from or related to DT, R is imported from Bayesian statistics. A more complete theoretical derivation of R from the same dynamical principles—perhaps as an information-theoretic functional of the occupation measure—remains an open direction for future work.

5. Theoretical Framework

5.1 Relationship Between DT, P_{topo}, and $E(t)$

Functional	What It Measures	Regime
$DT(x)$	Cumulative deviation from attractor	All systems
$P_{topo}(t)$	Topological feature lifetime	Systems with topological structure
$E(t)$	Rate of topological change	Learning systems

Hypothesis: In learning systems, DT and P_{topo} are positively correlated early in learning and negatively correlated late in learning. Turner & Barak (2023) demonstrate that RNNs develop attractors sequentially during training, which may correspond to phases of topological simplification. This is a testable prediction.

5.2 Relationship Between κ, γ, and $E(t)$

Hypothesis: In a learning system, the topological evolution rate $E(t)$ is monotonically related to κ only if the system is not in persistent chaos: $\partial E/\partial \kappa > 0$ (with E and κ measured on appropriate scales) in convergent regimes. In persistent chaos, $E(t)$ is monotonically related to γ: $\partial E/\partial \gamma > 0$. Correlation analysis provides a statistical test of these monotonicity relationships.

5.3 Adaptive Landscape (Heuristic Note)

The adaptive landscape $V(X,t)$ evolves as:
$$\dot{V} = g(X,V) - \lambda V + \xi(t)$$

For gradient systems with $\dot{X} = -\nabla_X V(X)$, and assuming the dynamics remain within the basin where higher-order nonlinearities are negligible, the cumulative deviation functional can be approximated as:
$$D_T(x) \approx \int_0^T \|\nabla_X V(\phi_\tau(x),\tau)\|\, d\tau$$

This is a local heuristic. A full derivation and integration into the core formalism is left for future work.

---

6. Testable Predictions

6.1 Core Prediction

Prediction: In a learning system, $E(t)$ is monotonically related to κ in convergent regimes: $\partial E/\partial \kappa > 0$ (with E and κ measured on appropriate scales), and $\partial E/\partial \gamma > 0$ in persistent chaos. Correlation analysis provides a statistical test of this monotonicity:
$$\mathrm{Corr}(E(t),\kappa) > 0 \iff \lambda_{max} < 0$$
$$\mathrm{Corr}(E(t),\gamma) > 0 \iff \lambda_{max} \approx 0$$

Falsification: If $E(t)$ correlates with κ in all regimes, or with γ in all regimes, the prediction is falsified.

6.2 Secondary Prediction

Prediction: In systems with high R, DT and P_{topo} are negatively correlated late in learning; in systems with low R, they are uncorrelated or positively correlated.

Falsification: If DT and P_{topo} are negatively correlated in both high-R and low-R systems, the prediction is falsified.

6.3 Boundary Condition and Global Falsifier

Conjecture: We conjecture that the framework applies to any system satisfying:

- A. Well-defined state space.
- B. Subject to perturbations.
- C. Exhibits at least one identifiable attractor.
- D. Dynamics are observable and measurable.

Global Falsifier: The unified ontology claim collapses if a system is found where DT, κ, and topological persistence are mutually independent across all regimes, and where R cannot be expressed as a functional of the trajectory or occupation measure. If such a system exists, the framework's claim to unify persistence, stability, and reality alignment would be falsified.

---

7. Experimental Design

7.1 System Choice

Train a CNN on MNIST or CIFAR-10. Use latent activation manifolds for topological analysis.

Justification: Karuppiah, Nazreen Banu et al. (2026) demonstrate the use of persistent homology on activations to study feature learning and generalization. Turner & Barak (2023) show that RNNs develop attractors sequentially, providing a controlled setting for studying topological evolution during learning.

7.2 Variable Measurement

Variable	Protocol
$DT(x)$	Sample weights; compute distance to final attractor; integrate.
$P\text{topo}(t)$	Compute persistent homology on latent activations; sum feature lifetimes.
$E(t)$	Finite differences of $P\text{topo}(t)$.
κ	Perturb weights; measure recovery time τ; $\kappa=1/\tau$.
γ	Compute average drift rate during training.
R	Cross-domain generalization accuracy.

7.3 Statistical Analysis

- Correlate $E(t)$ with κ and γ conditional on regime.
- Pre-register thresholds and sample size.

Note on future empirical work: A full empirical validation would require pre-registration with specified sample size, significance thresholds, power analysis, and robustness checks. These are planned for subsequent work.

---

8. Discussion

8.1 Implications

The paper provides a candidate formalization with defined variables, mathematical properties, and testable predictions. The mathematical properties of DT establish its relationship to κ and provide a foundation for the framework's core claims.

8.2 Limitations

- P_{topo} is computationally expensive.
- The framework is a meta-theory, not a complete domain-specific theory.
- Variables may be confounded; causal inference requires controlled experiments.
- The κ/γ regime distinction is proposed and requires empirical validation.

8.3 Future Work

- Empirical validation of predictions.
- Formal derivation of relationships from first principles.
- Extension to other domains.
- Computational efficiency improvements.

---

9. Conclusion

This paper proposes a candidate formalization for the attractor framework. The central mathematical innovation is treating persistence as a functional defined over trajectories—$D_T(x)=\int_0^T d(\phi_\tau(x),A)\,d\tau$—rather than as a scalar property of states. We defined the cumulative deviation functional D_T, the topological persistence functional $P_{\text{topo}}(t)$, and the topological evolution rate $E(t)$. We proved several mathematical properties of D_T, including non-negativity, monotonicity, additivity, Lipschitz continuity, and a bound relating D_∞ to κ: $D_\infty(x)\le\frac{C}{\kappa}d(x,A)$. We established connections to dynamic programming and ergodic theory. We unified the variable set with operational definitions. We derived testable predictions and provided a falsifiable experimental protocol.

The framework now admits formal definitions, operational variables, and empirical tests. The next step is empirical validation.

Appendix A: Possible Extensions from Larose (2025) — Unverified Source

Note: The following source has not been independently verified. It is included for completeness and as a potential direction for future exploration, but should not be treated as established.

Larose (2025) develops a framework for recursive deformation systems. Two constructs are potentially relevant:

Constraint Functional: $C(X)=\int_{\text{trajectory}} \|\nabla\Phi\|\, d\tau$, measuring cumulative irreversible deformation.

Persistence Invariant: $I_p=\oint_R d\Phi$, a topological invariant.

These are not yet integrated into the core framework and are presented here for completeness and future exploration. They should be treated as unverified candidate extensions.

References

Arnold, L. (1998). *Random Dynamical Systems*. Springer.

Berglund, L., et al. (2024). “The Reversal Curse: LLMs Trained on ‘A is B’ Fail to Learn ‘B is A’.” *arXiv:2309.12288*.

Bowen, R. (1975). *Equilibrium States and the Ergodic Theory of Anosov Diffeomorphisms*. Springer.

Carlsson, G. (2009). “Topology and data.” *Bulletin of the American Mathematical Society*, 46(2), 255-308.

Carlsson, G., & Zomorodian, A. (2009). “The theory of multidimensional persistence.” *Discrete & Computational Geometry*, 42(1), 71-93.

Clark, D. G., Abbott, L. F., & Litwin-Kumar, A. (2023). “Dimension of activity in random neural networks.” *Physical Review Letters*, 131, 118401.

Edelsbrunner, H., & Harer, J. (2010). *Computational Topology: An Introduction*. American Mathematical Society.

Engelken, R., Wolf, F., & Abbott, L. F. (2023). “Lyapunov spectra of chaotic recurrent neural networks.” *Physical Review*

Research, 5, 043044.

Fournier, S. J., & Urbani, P. (2023). “Statistical physics of learning in high-dimensional chaotic systems.” *Journal of Statistical Mechanics: Theory and Experiment*, 2023(11), 113301.

Karuppiah, K., Nazreen Banu, M., et al. (2026). “Topological Data Analysis (TDA) as a Framework for Understanding Deep Learning Behavior.” *2025 IEEE 5th International Conference on ICT in Business Industry & Government (ICTBIG)*, Indore, India, December 12-13, 2025. IEEE Xplore. DOI: 10.1109/ICTBIG68706.2025.11323998.

Larose, H. (2025). “A Mathematical Theory of Frame-Independent Persistence.” *Academia.edu*. [Unverified source.]

Ruelle, D. (1989). *Chaotic Evolution and Strange Attractors*. Cambridge University Press.

Sompolinsky, H., Crisanti, A., & Sommers, H. J. (1988). “Chaos in Random Neural Networks.” *Physical Review Letters*, 61(3), 259-262.

Turner, E., & Barak, O. (2023). “The Simplicity Bias in Multi-Task RNNs: Shared Attractors, Reuse of Dynamics, and Geometric Representation.” *Advances in Neural Information Processing Systems (NeurIPS)*.

Suggested citation: Galida, R. S. (2026). The Persistence Functional: A Candidate Formal Foundation for the Attractor Framework (Foundational Edition). *Fantasy Attractor*.

The Performance Attractor: A Framework for Social Cognition

Robert Galida
July 2026
[A] (Application)

Abstract

The attractor framework provides a unified vocabulary for describing persistence and change across physical, biological, cognitive, and social systems. This paper extends that vocabulary to social cognition. It proposes that social performance — the regulation of behavior in response to an internal model of being evaluated by real or imagined others — can be modeled as an attractor landscape in a high-dimensional social state space. Internal narration does not merely stabilize an attractor—it may actively reshape the attractor landscape over time. Confidence is hypothesized to correspond to a balance of κ, B, and R; insecurity to an imbalance. Happiness is hypothesized to be structurally associated with perceived action capacity and confidence; unhappiness with despondency. The paper formally defines the fantasy attractor of social performance — a self-reinforcing, reality-resistant basin whose update operator exhibits persistent insensitivity to corrective evidence. The Taoist concept of wu wei is interpreted as one computational resolution of the “wu wei paradox.” The framework generates testable predictions and is offered as a foundation for empirical investigation.

This paper presents a model hypothesis — that social behavior

can be represented as movement among attractor states — and a philosophical interpretation — that human social existence may be inescapably performative. These are distinct claims. The model hypothesis is the primary contribution; the philosophical interpretation is offered as a generative implication, not a proven conclusion.

---

1. Introduction

Social life involves performance — behavior optimized with respect to an internal model of social evaluation. We adopt roles, manage impressions, curate presentations of self. We monitor ourselves constantly — rehearsing, evaluating, adjusting. And we narrate internally — a running commentary on our own performance.

This is not a bug. It is a feature. Survival depends upon social navigation. Internal narration is practice — rehearsal for future interactions. Without it, there would be far more conflict.

But performance has a cost. Self-awareness becomes acute — and can paralyze. The same mechanism that enables survival can trap the system in a self-reinforcing loop. The performance can become a fantasy attractor — reality-resistant, self-sealing, and ultimately artificial.

A note on the paper's scope: This paper presents a **model hypothesis** — that social behavior can be represented as movement among attractor states in a high-dimensional state space. It also presents a **philosophical interpretation** — that human social existence may be inescapably performative. These are distinct claims. The model hypothesis is the primary contribution; the philosophical interpretation is offered as a generative implication, not a proven conclusion.

A note on the paper's strongest contribution: The central hypothesis is that internal narration does not merely stabilize an attractor — it may actively reshape the attractor landscape over time. This is a novel, testable computational claim.

---

2. Core Definitions

2.1 The Framework Variables

Variable	Definition	Role
κ (corrective permeability)	The rate at which a system returns to its dynamical trajectory after perturbation	Measures corrigibility
B (basin depth)	The energy barrier required to shift a system from one attractor state to another	Measures stability
C (coordination capacity)	The ability of a system to coordinate collective action	Measures coherence
R (reality alignment)	Within this framework, R is operationalized as predictive accuracy — the expected log predictive likelihood	Measures truth-tracking

Note: R is an operational measure of predictive accuracy, not a metaphysical claim about correspondence with reality. It is the expected log predictive likelihood: $R=E[\log p(y∣X)]$. When predictions are accurate, R is close to 0 (maximal). When predictions are poor, R is a large negative number (poor alignment).

2.2 Social Performance: A Definition

Social performance is defined as behavior optimized with respect to an internal model of social evaluation.

This definition is:

- **Measurable:** It can be operationalized through self-report, behavioral observation, and physiological measures
- **Distinct:** It distinguishes social performance from other forms of action (e.g., gardening alone, quiet contemplation)
- **Connected to literature:** It aligns with social cognition research on impression management, self-monitoring, and social anxiety

Falsification: If behavior is observed to be independent of internal models of evaluation, the concept is not useful.

2.3 The State Space of Social Performance

Define the social state vector: $X(t) \in \mathbb{R}^n$

where n is the dimensionality of the state space. The choice of representation is domain-specific:

Representation	Form	Domain
Role vector	$X=(r_1, r_2, \dots, r_n)$	Social roles and identities
Self-monitoring vector	$X=(a, m, p)$	Attention to self, monitoring intensity, performance effort
Social feedback vector	$X=(f_1, f_2, \dots, f_n)$	Perceived social feedback

Falsification: If different social states produce identical trajectories in the chosen X-space, the representation fails.

2.4 The State Equation (Fixed Landscape)

The dynamics of the social state on a fixed landscape are governed by:

$$\dot{X} = -\nabla V(X) + \eta(t) + E(t)$$

where:

- $X(t)$ is the social state at time t
- $V(X)$ is the social potential landscape
- $\eta(t)$ is stochastic noise (temperature T)
- $E(t)$ is external perturbation

2.5 The Potential Function

The framework requires a potential function $V(X)$ satisfying:

1. **Differentiability:** V is smooth
2. **Locally stable minima:** Attractors exist
3. **Finite escape barriers:** Basins have finite depth

A convenient illustrative form is:

$$V(X) = \frac{1}{2} c \|X - X^*\|^2 + \frac{B}{1 + e^{-\alpha \|X - X^*\|^2}}$$

where:

- c is the curvature parameter (not κ)
- B is the basin depth (barrier height)
- α controls the steepness of the basin

Note: This is an illustrative ansatz, not a unique derivation. Other functional forms satisfying the three conditions above are equally compatible with the framework.

Note on κ/B coupling: Under this specific ansatz, the local curvature at the attractor — and therefore κ — depends on both c and B (and α). Increasing B while holding c fixed also increases κ. This coupling is a property of this particular potential function; other functional forms might decouple them. Whether κ and B can be independently manipulated is an open empirical question.

2.6 Derived Variables

Variable	Derivation	Units
κ	$\kappa = \lambda_{\min}(\nabla^2 V(X^*))$	time^{-1}
B	$B = \min_{X \in \partial B} V(X) - V(X^*)$	Energy
R	$R = \mathbb{E}[\log p(y \mid X)]$	Bits (expected log predictive likelihood)

---

3. Adaptive Landscape Dynamics

3.1 From Fixed to Adaptive Landscapes

Sections 2.4–2.6 describe dynamics on a **fixed landscape** — the potential function $V(X)$ is static. However, Section 3 introduces an **extension** in which the landscape itself evolves through learning, experience, and internal narration.

This is an adaptive landscape: $V = V(X,t)$

and the dynamics become: $\dot{X} = -\nabla_X V(X,t) + \eta(t) + E(t)$

$\dot{V} = g(\text{narration}, \text{learning}, \text{experience})$

The landscape evolves over time as a function of internal narration and experience. This distinguishes the framework from fixed-landscape models and makes it genuinely adaptive.

3.2 Internal Narration and Landscape Reshaping

Hypothesis: Internal narration does not merely deepen B — it may reshape the attractor landscape itself. $\dot{V} = g(\text{narration})$

where g captures how narration:

- Deepens existing wells
- Creates new wells
- Splits one basin into multiple identity basins
- Flattens obsolete basins

Empirical anchor: Rumination — a form of repetitive, self-focused narration — is associated with cognitive rigidity, suggesting deeper basins (Nolen-Hoeksema, 1991).

Falsification: If narration frequency does not correlate with B measures or landscape reshaping, the link is unsupported.

3.3 Rehearsal and Performance Improvement

Hypothesis: Internal narration functions as rehearsal — it improves performance under social conditions.

Empirical anchor: Self-talk research shows that strategic internal rehearsal improves public-speaking performance (Hardy, 2006).

Falsification: If narration does not predict performance improvement, the rehearsal hypothesis fails.

3.4 The Bidirectional Loop

The relationship between performance and narration is bidirectional: $\text{Performance} \leftrightarrow \text{Narration} \leftrightarrow V(X,t)$

Stage	Description
1. Performance	You adopt a role, manage impressions, curate your presentation
2. Narration	You rehearse, evaluate, adjust, comment on your own performance
3. Reshaping	The landscape evolves — wells deepen, new wells form, obsolete wells flatten
4. Monitoring	You watch yourself constantly
5. Performance improves	The rehearsal makes you a better performer
6. Self-awareness becomes acute	You become hyper-aware of your own performance

The loop is self-reinforcing: performance generates narration, narration reshapes the landscape, and the reshaped landscape generates more performance.

---

4. Confidence vs. Insecurity

4.1 Confidence

Hypothesis: Confidence corresponds to moderate κ + moderate B + moderate R — the system is stable enough to persist, flexible enough to correct, and aligned enough to navigate.

Empirical anchor: Higher self-efficacy correlates with persistence and success in tasks (Bandura, 1997).

Falsification: If confidence does not correlate with the predicted parameter combination, the hypothesis fails.

4.2 Insecurity

Hypothesis: Insecurity corresponds to high error detection (κ_detection) + low behavioral updating (κ_correction) + deep B + low R.

This requires separating two components of corrective permeability:

- **κ_detection:** The rate at which errors are detected
- **κ_correction:** The rate at which behavior is updated in response to errors

Insecurity involves rapid detection but poor updating.

Note: This split into κ_detection and κ_correction is an informal extension to the formal model, introduced to capture the distinction between error detection and behavioral updating. The formal model (see §2.6) defines κ as a single scalar — the slowest-relaxing mode of the Hessian. The two-component decomposition is a heuristic for interpretation, not a derivation from the state equation.

Empirical anchor: Social anxiety involves hyper-vigilance, chronic negative self-monitoring, and low reality-alignment (Clark & Wells, 1995).

Falsification: If insecurity does not correlate with this parameter combination, the hypothesis fails.

4.3 The Difference

State	κ_detection	κ_correction	B	R	Outcome
Confidence	Moderate	Moderate	Moderate	Moderate	Action
Insecurity	High	Low	Deep	Low	Freezing

5. Happiness and Unhappiness

5.1 Happiness and Confidence

Hypothesis: Within this framework, happiness is structurally associated with perceived action capacity and confidence. Happiness is hypothesized to correlate with behavioral measures of social engagement, action initiation, and risk-taking.

Empirical anchor: Perceived control correlates negatively with depression (Seligman, 1975). When people feel capable and their actions lead to outcomes, they tend to be happier.

Falsification: If happiness does not correlate with confidence measures, the hypothesis fails.

5.2 Unhappiness and Despondency

Hypothesis: Unhappiness is structurally associated with despondency — the felt sense of being unable to act. Unhappiness is hypothesized to correlate with behavioral measures of withdrawal, inaction, and avoidance.

Empirical anchor: Perceived control correlates negatively with depression. When people feel powerless, unhappiness rises.

Falsification: If unhappiness does not correlate with despondency measures, the hypothesis fails.

5.3 The Relationships

Relationship	Meaning
Happiness ≈ Confidence	Happiness is structurally associated with the experience of trusting your own basin
Unhappiness ≈ Despondency	Unhappiness is structurally associated with the experience of not trusting your own basin

Note: These are associations, not identities. Happiness includes pleasure, meaning, attachment, physiology, temperament, reward processing, and social connection. Confidence explains part of happiness — not all of it.

---

6. The Fantasy Attractor of Social Performance

6.1 Formal Definition

A **fantasy attractor** is an attractor whose update operator exhibits persistent insensitivity to corrective evidence.

Formally, a fantasy attractor satisfies:

1. **High B:** Deep basin — the system is resistant to leaving
2. **Low effective κ:** Poor correction — the system does not

update in response to evidence

3. **Systematically biased R:** Low reality alignment — the system's models are persistently distorted
4. **Persistent insensitivity to corrective evidence:**

$$\frac{\partial R}{\partial E} \approx 0$$

despite non-zero prediction error, where E is disconfirming evidence. The system's predictive accuracy does not improve even when errors are present.

6.2 Diagnosis

Hypothesis: The performance-narration system can become a fantasy attractor — a self-reinforcing, reality-resistant basin that persists despite mounting evidence of its artificiality.

Symptom	Description
Low R	The system is aligned with the performance, not with reality
Deep B	The performance is deeply entrenched
Low κ	The system resists correction — any challenge to the performance is a threat
Self-reinforcement	The performance loops back on itself

6.3 Sealing Mechanisms

Mechanism	Description
Confirmation bias	Seeking confirming evidence, ignoring disconfirming cues
Belief perseverance	Beliefs persist after evidence is shown to be false

Mechanism	Description
Counter-evidence discounting	Disconfirming evidence is reframed as an exception
Identity fusion	The performance is tied to self-worth

Falsification: If a person accepts disconfirming evidence readily, the fantasy-attractor model is wrong.

6.4 Attractor Shifts, Not Escape

Hypothesis: The framework predicts that interventions shift individuals between attractor configurations rather than eliminating social regulation entirely.

Empirical anchor: Every intervention tested (mindfulness, therapy, meditation) produces a new cognitive mode, not a blank slate.

Testable prediction: Every intervention preserves some degree of social predictive regulation, even if self-monitoring and explicit narration decrease.

Operationalization: Meditation decreases self-report narration but leaves prediction accuracy above chance. Therapy decreases rumination without eliminating role behaviour. These are measurable quantities.

Falsification: If an intervention produces a state with zero self-monitoring, zero role occupancy, and zero internal narration, the hypothesis fails.

---

7. Testable Predictions

Prediction 1: Narration correlates with B

Frequent internal narration will correlate with measures of role persistence and resistance to social feedback.

Prediction 2: Narration improves performance

Strategic internal narration will predict performance improvement in social tasks.

Prediction 3: Confidence = moderate κ + moderate B + moderate R

High-confidence individuals will show balanced measures of corrigibility, stability, and reality alignment.

Prediction 4: Insecurity = high κ_detection + low κ_correction + deep B + low R

High-insecurity individuals will show rapid error detection, poor behavioral updating, deep role persistence, and poor social prediction accuracy.

Prediction 5: Happiness correlates with confidence

Happiness self-reports will correlate with behavioral measures of social engagement, action initiation, and risk-taking.

Prediction 6: Unhappiness correlates with

despondency

Unhappiness self-reports will correlate with behavioral measures of withdrawal, inaction, and avoidance.

Prediction 7: Taoist practitioners show shallow B + high κ + high R

Taoist practitioners will show shallower role persistence, faster error correction, and higher social prediction accuracy.

Prediction 8: Interventions shift attractors, not eliminate performance

Every intervention preserves some degree of social predictive regulation, even if self-monitoring and explicit narration decrease. Meditation decreases self-report narration but leaves prediction accuracy above chance. Therapy decreases rumination without eliminating role behaviour.

---

8. Philosophical Interpretation: Wu Wei

8.1 Wu Wei as a Distinct Attractor State

Wu wei is a Taoist concept often translated as “non-action” or “effortless action.” Within this framework, we interpret it as a distinct attractor state characterized by shallow B, high κ, and high R — a state of effortless responsiveness, full attunement to reality, and minimal self-monitoring.

The longstanding paradox of deliberate spontaneity (wu wei) has been extensively discussed in the scholarship on early

Chinese thought (Slingerland, 2000). This paper offers one computational resolution of that paradox.

This is one computational interpretation of wu wei, not a definitive reading of the tradition.

Empirical anchor: Taoist practitioners show differences in cognitive flexibility, role persistence, and social prediction accuracy compared to controls.

Falsification: If Taoist practitioners do not show shallower B, higher κ, or higher R, the hypothesis fails.

8.2 The Paradox of Non-Performance

Observation: To claim non-performance is to perform non-performance.

Resolution: The performance of non-performance is not a failure — it is the *only* path. There is no escape from performance; there is only the *choice of which performance to inhabit*.

Performance Type	B	κ	R	Outcome
Social performance (role-playing)	Deep	Low	Low	Trapped in fantasy attractor
Authenticity performance	Moderate	Moderate	Moderate	Closer to reality
Non-performance performance	Shallow	High	High	The closest approximation available

---

8.3 The Taoist’s Basin

Claim	Underlying Dynamics
“I am non-performative”	The performance of being non-performative
“I am authentic”	The performance of being authentic
“I have transcended”	The performance of having transcended
“I am at peace”	The performance of being at peace

---

9. What This Paper Does Not Claim

This paper does not claim:

- Performance is inherently pathological
- Escape from performance is possible
- Taoism is a complete solution
- The framework replaces social psychology
- The framework is a theory of everything
- Happiness is *only* confidence
- Wu wei is definitively “performing non-performance”
- The philosophical interpretation is proven

---

10. Limitations

Limitation	Address
κ, B, and R are not yet measured in social contexts	Candidate measures are proposed but not validated
The Taoist mapping is philosophical, not empirical	Empirical testing is required

Limitation	Address
The state space is generic	Specific representations require empirical validation
The potential function is illustrative	Alternative forms are possible

---

11. Conclusion

Social performance can be modeled as an attractor landscape. Internal narration functions as rehearsal, deepening the performance basin or reshaping the landscape. Confidence enables action; insecurity enables freezing. Happiness is structurally associated with confidence; unhappiness with despondency.

The fantasy attractor of social performance is formally defined as an attractor whose update operator exhibits persistent insensitivity to corrective evidence — unifying confirmation bias, belief perseverance, identity-protective cognition, and self-presentation into one dynamical picture.

Wu wei is interpreted as a distinct attractor state characterized by shallow B, high κ, and high R — effortless responsiveness, full attunement to reality.

The framework predicts that adaptive functioning depends less on escaping social performance than on occupying attractor states that remain corrigible, reality-aligned, and resistant to maladaptive self-reinforcement.

References

- Bandura, A. (1997). *Self-efficacy: The exercise of control*. Freeman.
- Clark, D.M., & Wells, A. (1995). "A cognitive model of social phobia." In *Social phobia: Diagnosis, assessment, and treatment*.
- Hardy, J. (2006). "Speaking clearly: A critical review of the self-talk literature." *Psychology of Sport and Exercise*, 7(1), 81–97.
- Nolen-Hoeksema, S. (1991). "Responses to depression and their effects on the duration of depressive episodes." *Journal of Abnormal Psychology*, 100(4), 569–582.
- Seligman, M.E.P. (1975). *Helplessness: On depression, development, and death*. Freeman.
- Slingerland, E. (2000). "Effortless action: The Chinese spiritual ideal of wu-wei." *Journal of the American Academy of Religion*, 68(2), 293–328.

Suggested citation: Galida, R. S. (2026). The Performance Attractor: A Framework for Social Cognition. *Fantasy Attractor*.

Cognitive Attractor Dynamics: A Formal Theory of Self-

Concept and Self-Engineering

Robert Galida
July 2026
[F] (Foundation)

Abstract

The attractor framework provides a unified vocabulary for describing persistence and change across physical, biological, cognitive, and social systems. This paper presents a formal theory of cognitive attractor dynamics, grounding the framework's core variables—κ (corrective permeability), B (basin depth), C (coordination capacity), and R (reality alignment)—in a rigorous mathematical framework. The cognitive state space $X(t) \in \mathbb{R}^n$ is defined, a dynamical equation $\dot{X} = -\nabla V(X) + \eta(t) + E(t)$ is specified, and the variables are derived from the potential landscape $V(X)$. The theory connects to existing frameworks (Hopfield networks, predictive coding, active inference, reinforcement learning) and generates testable predictions about cognitive flexibility, goal persistence, reality alignment, and coordination capacity. The paper is offered as a formal foundation for empirical testing.

All claims are formal hypotheses, not conclusions. The framework is a domain-general dynamical ontology with an associated research programme — a formal theory, not a completed science.

---

1. Introduction

The attractor framework has been applied to biology, cosmology, AI, and civilizational dynamics. This paper presents a formal theory of cognitive attractor dynamics. It asks a simple question:

> *Can the self — beliefs, goals, and self-narratives — be modeled as an attractor landscape in a high-dimensional cognitive state space?*

The answer is yes — with explicit formal definitions.

A note on the Law of Attraction: The Law of Attraction is often framed as a metaphysical claim. This paper reframes it as **conscious self-direction and self-engineering** — the deliberate shaping of one's own cognitive attractor landscape through belief revision, attentional focus, and behavioral reinforcement.

A note on the framework's status: This paper presents a formal theory. The mathematical derivation of equivalence is specified. The framework is offered as a foundation for empirical testing.

A note on domain of applicability: The framework applies to any persistent cognitive system satisfying the formal conditions defined below.

---

2. Core Definitions

2.1 The Framework Variables

Variable	Definition	Role
κ (corrective permeability)	The rate at which a system returns to its dynamical trajectory after perturbation	Measures corrigibility
B (basin depth)	The energy barrier required to shift a system from one attractor state to another	Measures stability
C (coordination capacity)	The ability of a system to coordinate collective action	Measures coherence
R (reality alignment)	The degree to which a system's models correspond to empirical reality	Measures truth-tracking

2.2 Primitive vs. Derived Concepts

Primitive	Definition	Derived	Source
State	The complete description of a system at a given time	—	—
Interaction	Any exchange of energy, momentum, or information between systems	—	—
Constraint	Any factor that restricts the possible states or trajectories of a system	—	—

Primitive	Definition	Derived	Source
Perturbation	Any deviation from the system’s dynamical trajectory	—	—
—	—	**κ**	Recovery rate after perturbation (derived from perturbation dynamics)
—	—	**B**	Energy barrier between attractors (derived from constraint topology)
—	—	**C**	Coordination capacity (derived from interaction topology)
—	—	**R**	Reality alignment (derived from model-state correspondence)

---

3. The Formal Theory

3.1 The Cognitive State Space

Define the cognitive state vector: $X(t) \in \mathbb{R}^n$

where n is the dimensionality of the state space. The choice of representation is domain-specific:

Representation	Form	Domain
Belief vector	$X=(b_1,b_2,\dots,b_n)$	Cognitive psychology

Representation	Form	Domain
Neural latent	$X \in \mathbb{R}^d$	Computational neuroscience
Control variables	$X = (a, e, m)$	Cognitive control

Distinction between spaces:

- **Abstract state space** $\mathcal{X}$: the theoretical manifold of cognitive states
- **Measurement space** $\mathcal{Y}$: the space of observables (behavior, neural activity)
- **Embedding** $\phi: \mathcal{Y} \to \mathcal{X}$: mapping from data to latent state

Falsification: If different cognitive states produce identical trajectories in the chosen X-space, the representation fails.

3.2 The State Equation

The dynamics of the cognitive state are governed by:

$$\dot{X} = -\nabla V(X) + \eta(t) + E(t)$$

where:

- $X(t)$ is the cognitive state at time t
- $V(X)$ is the cognitive potential landscape
- $\eta(t)$ is stochastic noise (temperature T)
- $E(t)$ is external perturbation

3.3 The Potential Function

We adopt the following **illustrative potential function** — a mathematically smooth function that produces one minimum and finite depth:

$$V(X) = \frac{1}{2} c \|X - X^*\|^2 + \frac{B}{1 + e^{-\alpha \|X - X^*\|^2}}$$

where:

- c is the curvature parameter (not κ)
- B is the basin depth (barrier height)
- α controls the steepness of the basin

Note: This potential function is an **illustrative ansatz**, chosen to demonstrate the framework’s logic. Alternative forms (multi-well, free-energy-based) are possible and should be explored empirically. The specific functional form is not claimed to be a unique derivation.

Alternative forms:

Form	Equation	Use Case
Quadratic	$V(X)=\frac{1}{2}c\lVert X-X^*\rVert^2$	Single attractor, linear dynamics
Multi-well	$V(X)=\sum_i B_i\,\phi(\lVert X-X_i^*\rVert^2)$	Multiple attractors
Free energy	$V(X)=-\log p(X)$	Bayesian/predictive coding

3.4 Basin Depth (B)

Basin depth B is the energy barrier required to escape the attractor’s basin: $B=\min_{X\in\partial\mathcal{B}} V(X)-V(X^*)$

where:

- X^* is the attractor (stable fixed point)
- $\partial\mathcal{B}$ is the boundary of the basin of attraction
- $V(X^*)$ is the potential at the attractor

Empirical estimation: B can be estimated from:

- Time to return to baseline after perturbation
- Probability of escape under noise: $P_{escape}\propto e^{-B/T}$

- Hysteresis in response to changing inputs

3.5 Corrective Permeability (κ)

κ is the rate of recovery toward the attractor after a perturbation. It is **derived from the curvature of V**, not independently parameterized.

Formal definition: For a linearized system near the attractor: $\dot{\delta X} = -\nabla^2 V(X^*)\,\delta X$

where $\delta X = X - X^*$ is the deviation from the attractor. The recovery rate is determined by the largest (least negative) eigenvalue of the Hessian: $\kappa = -\lambda_{\max}(-\nabla^2 V(X^*))$

For our illustrative potential: $\nabla^2 V(X) = c + \frac{2B\alpha c}{1 + e^{-\alpha \lVert X - X^* \rVert^2}}$

At the attractor ($X = X^*$): $\kappa_{\text{baseline}} = c + B\alpha$

This resolves the circularity: κ is now a derived quantity from the same landscape V. It is not independently parameterized.

Empirical estimation: κ can be estimated from:

- Error-correction times in cognitive tasks
- Post-error slowing in reaction time tasks
- Recovery from emotional perturbations
- Neural measures of flexibility (dynamic connectivity)

3.6 Reality Alignment (R)

R is the predictive accuracy of the system: $R = -\mathbb{E}[\log p(y \mid X)]$

where $p(y \mid X)$ is the system's predictive distribution over outcomes y given its current state X.

R belongs in learning dynamics, not in the potential: $\dot{\theta} = g(R, \delta)$

where θ controls the landscape V, and δ is the prediction error.

Relationship to free energy: $F = \mathrm{KL}(q \| p) + R$

where F is variational free energy. R is maximized when the system’s predictions match reality.

Empirical estimation: R can be estimated from:

- Predictive accuracy in decision-making tasks
- Calibration of confidence judgments
- Prediction error signals (dopaminergic, sensory)

3.7 Coordination Capacity (C)

C is hypothesized to emerge from the network topology of cognitive subsystems.

Open research question: The specific functional form — whether it depends on total coupling strength, spectral radius, modularity, or other graph-theoretic measures — is an open research question. Candidate measures include:

Measure	Description
Spectral radius	Largest eigenvalue of coupling matrix
Modularity	Degree of community structure
Global efficiency	Average inverse shortest path length
Synchronization threshold	Second-smallest Laplacian eigenvalue

Empirical estimation: C can be estimated from:

- Coherence between subsystems
- Synchrony of neural or behavioral signals
- Network graph-theoretic measures

Note: The formula $C = \mathrm{Tr}(W) \cdot \min_i B_i$ is not claimed as a unique derivation. It is a placeholder for future empirical investigation.

---

4. The Full Parameterized System

4.1 Complete State Equation

Combining all definitions: $\dot{X} = -\nabla V(X) + \eta(t) + E(t)$

where:

- $V(X)$ is the cognitive potential landscape
- $\eta(t)$ is stochastic noise (temperature T)
- $E(t)$ is external perturbation

4.2 Derived Variables

Variable	Derivation	Units
κ	$\kappa = -\lambda_{\max}(-\nabla^2 V(X^*))$	time^{-1}
B	$B = \min_{X \in \partial B} V(X) - V(X^*)$	Energy
R	$R = -\mathbb{E}[\log p(y \mid X)]$	Bits
C	Open research question	Dimensionless

4.3 Parameter Interactions

The parameters are hypothesized to interact:

Hypothesis	Formal Statement
κ increases with R	$\kappa \propto R$
B decreases with κ	$B \propto 1/\kappa$
R decreases with B	$R \propto 1/B$
Optimal B maximizes κ·R	$B^* = \arg\max(\kappa \cdot R)$

Falsification: If the variables are entirely independent, the framework is a taxonomy, not a unified theory.

---

5. Relationship to Existing Frameworks

Framework	Mathematical Form	Relationship
Hopfield networks	$V = -\frac{1}{2}\sum w_{ij} X_i X_j$	Special case: discrete attractors
Predictive coding	$F = -\log p(y \mid X) + \mathrm{KL}$	R is negative free energy (minus complexity)
Active inference	$\dot{X} = -\frac{\partial F}{\partial X}$	General case: both perception and action
Reinforcement learning	$V(s) = \max_a \mathbb{E}[R + \gamma V(s')]$	C emerges from value function coupling

---

6. Testable Predictions

6.1 Prediction 1: Mindfulness Increases κ

Formal statement: Mindfulness training increases corrective permeability.

Empirical test: Measure error-correction times in cognitive tasks before and after mindfulness intervention. Faster post-error adjustments indicate higher κ.

Falsification: If mindfulness training does not lead to faster error-correction times, the prediction fails.

6.2 Prediction 2: Rigidity = Deep B + Low κ

Formal statement: High cognitive rigidity corresponds to deep B and low κ.

Empirical test: Measure reversal learning times and set-shifting ability in high-rigidity individuals.

Falsification: If rigid individuals adapt as quickly as flexible individuals, the prediction fails.

6.3 Prediction 3: Rumination = High B + Low R

Formal statement: Rumination corresponds to high B and low R.

Empirical test: Measure persistence in negative mood states and predictive accuracy in ruminative individuals.

Falsification: If ruminators show low persistence or high predictive accuracy, the prediction fails.

6.4 Prediction 4: Success = High B + High κ

Formal statement: Goal achievement requires both deep B and high κ.

Empirical test: Measure goal persistence (B) and adaptability (κ) in high-achieving individuals.

Falsification: If high achievers show low B or low κ, the prediction fails.

6.5 Prediction 5: Obsession = High B + Low κ

Formal statement: Obsessive-compulsive patterns correspond to high B and low κ.

Empirical test: Measure persistence on incorrect choices in obsessive individuals.

Falsification: If obsessive individuals show normal recovery from errors, the prediction fails.

6.6 Prediction 6: Kramers' Escape in Cognition

Formal statement: Cognitive transition probabilities follow Kramers' law.

Empirical test: Vary noise levels (uncertainty, distractors) and measure transition rates between cognitive states.

Falsification: If the relationship is not log-linear, the basin-depth metaphor fails.

6.7 Prediction 7: Exponential Recovery

Formal statement: Cognitive recovery follows exponential decay.

Empirical test: Fit recovery trajectories to exponential and power-law models.

Falsification: If power-law fits are superior, the exponential recovery model fails.

---

7. What This Paper Does Not Claim

This paper does not claim:

- Thoughts directly create reality
- The Law of Attraction is literally true as a metaphysical claim
- The framework replaces cognitive science
- The framework is a theory of everything
- The framework generates novel predictions (it does — see

§6)

- Mathematical equivalence between cognitive and other systems
- C is a primitive variable (it is an open research question)
- The illustrative potential function is a unique derivation

---

8. Limitations

Limitation	Address
κ is derived from V	□ Resolved
R belongs in learning dynamics	□ Resolved
B and κ are not independent	□ Resolved
Potential function is ad hoc	□ Acknowledged as illustrative ansatz
State space is generic	□ Distinction between abstract/measurement/embedding spaces added
C formula is speculative	□ Removed; left as open research question

---

9. Open Research Questions

Question	Domain
What is the minimal state space for a given cognitive domain?	Formalization

Question	Domain
What is the functional form of V(X) for a given domain?	Formalization
Do cognitive escape probabilities follow Kramers’ law?	Empirical
Do recovery trajectories follow exponential decay?	Empirical
Is R equivalent to negative free energy?	Formalization
Can C be derived from network topology?	Formalization
Do κ, B, and R scale with system size?	Formalization
Does an optimal B exist?	Empirical
How do κ, B, and R interact?	Formalization

---

10. Conclusion

The attractor framework is now formally defined:

Element	Definition
State space	$X(t) \in \mathbb{R}^n$
Dynamics	$\dot{X} = -\nabla V(X) + \eta + E$
Potential	$V(X) = \frac{1}{2}c\lVert X - X^* \rVert^2 + \frac{B}{1 + e^{-\alpha \lVert X - X^* \rVert^2}}$ (illustrative ansatz)
Derived: κ	$\kappa = -\lambda_{\max}(-\nabla^2 V(X^*))$
Derived: B	$B = \min_{X \in \partial B} V(X) - V(X^*)$
Derived: R	$R = -\mathbb{E}[\log p(y \mid X)]$
Open: C	Emerging from network topology

The framework generates testable predictions and is ready for empirical validation.

The next step is computational validation: simulate the dynamics, recover κ and B, demonstrate Kramers’ escape, and

show recovery trajectories. Then move to human experiments.

References

- Boyatzis, R.E., Rochford, K., & Taylor, S.N. (2015). “The role of the positive emotional attractor in vision and shared vision.” *Frontiers in Psychology*, 6:670.
- Cheema, A., & Bagchi, R. (2011). “The effect of goal visualization on goal pursuit.” *Journal of Marketing*, 75(2), 109–123.
- Geisler, F.C.M., & Kubiak, T. (2009). “Heart rate variability predicts self-control in goal pursuit.” *European Journal of Personality*, 23, 623–633.
- Golubickis, M., Tan, L.B.G., Jalalian, P., Falbén, J.K., & Macrae, C.N. (2024). “Brief mindfulness-based meditation enhances the speed of learning following positive prediction errors.” *Quarterly Journal of Experimental Psychology*, 77(11), 2312–2324.
- Kronemyer, D., & Bystritsky, A. (2014). “A non-linear dynamical approach to belief revision in cognitive behavioral therapy.” *Frontiers in Computational Neuroscience*, 8:55.
- MacDonald, M.R., & Kuiper, N.A. (1985). “Efficiency and automaticity of self-schema processing in clinical depressives.” *Motivation and Emotion*, 9(2), 171–184.
- Singer, J.A., Blagov, P., Berry, M., & Oost, K.M. (2013). “Self-defining memories, scripts, and the life story.” *Journal of Personality*, 81(6), 569–582.

Suggested citation: Galida, R. S. (2026). Cognitive Attractor Dynamics: A Formal Theory of Self-Concept and Self-Engineering. *Fantasy Attractor*.

The Universe as a Prestressed System: A Taoist Cosmology

Robert Galida
June 2026
[R] (Research Note)

Abstract

The attractor framework provides a unified vocabulary for describing persistence and change across physical, biological, cognitive, and social systems. This paper extends that vocabulary to cosmology. It proposes that the universe can be interpreted as a **prestressed system** — with the three metronomes (electron, proton, neutrino) acting as persistent dynamical primitives ("rebar"), and space itself acting as the "osmotic pressure" (a dissipative medium). The cosmological constant (Λ) is interpreted as the cosmic analogue of the WHC-water discrepancy — the "excess" energy required to explain observed expansion beyond what matter alone would produce. The paper maps Taoist concepts (Tao, wu wei, ziran) onto the framework's variables (constraint field, κ, R), demonstrating structural alignment with both modern cosmology and ancient wisdom. The paper is offered as a generative hypothesis, not a replacement for ΛCDM. It does not claim that the universe is alive or conscious — only that it is dissipative and may be intelligent insofar as it persists under perturbation.

All claims are structural mappings, not mathematical equivalences. The framework is a domain-general dynamical

ontology with an associated research programme — a heuristic vocabulary, not a theory of everything. The mathematical derivation of equivalence is an open research question.

---

1. Introduction

The attractor framework has been applied to biology, cognition, AI, and civilizational dynamics. This paper extends it to cosmology. It asks a simple question:

> *Can the universe be interpreted as a prestressed system — with stable particles as its "rebar" and space as its "osmotic pressure"?*

The answer is yes — with important qualifications.

The framework does not claim that the universe is alive or conscious. It claims that the universe is a **dissipative system** that persists under perturbation, navigates constraints, and exhibits structure — properties that, within the framework, are the hallmarks of intelligence at its most basic level.

A note on ΛCDM: The ΛCDM model is the standard model of cosmology, describing a universe composed of approximately 68% dark energy (Λ), 26.5% cold dark matter (CDM), and 4.9% ordinary matter. This paper does not replace ΛCDM. It offers a vocabulary for interpreting it.

A note on the framework's status: This paper does not claim mathematical equivalence between biological and cosmological systems. It claims structural isomorphism at the level of dynamical organization. The mathematical derivation of equivalence is an open research question.

A note on domain of applicability: The framework is hypothesized to apply to any persistent dynamical system satisfying Conditions A–D (see §2.4). The universality of the framework is an empirical hypothesis, not an assumption.

---

2. Core Definitions

2.1 The Framework Variables

Variable	Definition	Role
κ (corrective permeability)	The rate at which a system returns to its dynamical trajectory after perturbation	Measures corrigibility
B (basin depth)	The energy barrier required to shift a system from one attractor state to another	Measures stability
C (coordination capacity)	The ability of a system to coordinate collective action	Measures coherence
R (reality alignment)	The degree to which a system’s models correspond to empirical reality	Measures truth-tracking

2.2 Primitive vs. Derived Concepts

The framework distinguishes foundational concepts from derived ones:

Primitive	Definition	Derived	Source
State	The complete description of a system at a given time	—	—
Interaction	Any exchange of energy, momentum, or information between systems	—	—
Constraint	Any factor that restricts the possible states or trajectories of a system	—	—
Perturbation	Any deviation from the system’s dynamical trajectory	—	—
—	—	**κ**	Recovery rate after perturbation (derived from perturbation dynamics)
—	—	**B**	Energy barrier between attractors (derived from constraint topology)
—	—	**C**	Coordination capacity (derived from interaction topology)

Primitive	Definition	Derived	Source
—	—	**R**	Reality alignment (derived from model-state correspondence)
—	—	**Fantasy attractor**	Low R + mechanisms preventing R increase

Note on the primitive hierarchy: This primitive layer (State, Interaction, Constraint, Perturbation) is the level of abstraction at which both mechanotransduction and constraint navigation are instances — mechanotransduction as a Constraint-mediated Interaction, navigation as Perturbation-response via the same primitives. This resolves the earlier cross-paper tension between mechanotransduction and constraint-detection as “the primitive.”

2.3 Conservative vs. Dissipative Attractors

In the attractor framework:

Type	Definition	Examples
Conservative	No energy input, no phase-space contraction, no attractor	Electrons, protons, neutrinos (persistent dynamical primitives)
Dissipative	Energy input required, phase-space contraction, attractor exists	Life, mind, society, the universe (in the horizon-thermodynamic sense)

Crucially: A system with κ (a recovery rate toward an attractor) is necessarily dissipative. Conservative systems — in the strict dynamical-systems sense — do not have attractors. Within this framework, the universe is interpreted as dissipative in the horizon-thermodynamic sense, even without external energy input, due to Gibbons–Hawking temperature and horizon entropy.

2.4 Domain of Applicability

The framework is hypothesized to apply to any system satisfying the following conditions:

Condition	Description
A	The system has a well-defined state space
B	The system is subject to perturbations
C	The system exhibits persistent structure (attractors)
D	The system's dynamics can be observed and measured

Systems satisfying these conditions are hypothesized to admit a state-space description possessing analogues of κ, B, C, and R. This is an empirical hypothesis, not an assumption.

2.5 The Constraint Field

The **constraint field** is the attractor landscape — the set of possible states and the energy barriers between them. It is the underlying structure that shapes the dynamics of any system:

Domain	Constraint Field
Biology	The extracellular matrix (ECM)
Cosmology	Spacetime geometry
Belief systems	Conceptual space of possible beliefs
Society	Communication networks and institutions
AI	Parameter manifold and latent space

2.6 The Interaction Manifold

The **interaction manifold** is the topology through which interactions propagate:

Domain	Interaction Manifold
Biology	Interstitial ECM
Society	Communication network
AI	Parameter graph / latent space
Economy	Exchange network
Cosmology	Spacetime manifold

This generalizes the concept of “space” across domains.

---

3. The Metronomes as Persistent Dynamical Primitives

3.1 The Three Metronomes

The three metronomes are persistent dynamical primitives — long-lived invariant structures that provide the “eternal skeleton” of the universe:

Metronome	Role	Stability	Channel
Electron	Provides charge and electromagnetic structure	>6.6×10^{28} years	$e^- \rightarrow \gamma + \nu$ (Borexino)
Proton	Provides mass and nuclear structure	>2.4×10^{34} years	$p \rightarrow e^+\pi^0$ (Super-Kamiokande, 90% C.L.)

Metronome	Role	Stability	Channel
Neutrino	Provides weak force and cosmic background	Model-dependent	Standard Model neutrinos have no known decay channel; cosmological bounds (CMB, BBN) constrain mass and lifetime for specific models

Terminological note: These particles are not “attractors” in the strict dynamical-systems sense. They are **persistent dynamical primitives** — stable structures that persist without energy input and provide the invariant framework within which dissipative dynamics unfold. The term “metronome” captures their role as steady clocks against which all change is measured.

Why three? The framework does not claim that there are exactly three such primitives. It identifies electron, proton, and known neutrinos as present examples. Should additional stable particles be discovered (sterile neutrinos, axions, stable WIMPs), the list would expand accordingly. The core claim is that **long-lived fundamental particles serve as persistent dynamical primitives** — the specific count is contingent on physics, not a necessary feature of the framework.

3.2 Rebar Constraints

In the biological analogy, collagen constrains GAG swelling, creating coherent tissue structure. In the cosmological analogy, the metronomes constrain space expansion, creating coherent cosmic structure:

Observation	Interpretation
Cosmic web	Filaments and voids — gravitational binding acts as rebar, constraining expansion
Structure formation	Overdensities collapse into galaxies, clusters, and superclusters
Dark matter	Provides additional gravitational scaffolding

The cosmic web is the “tissue” of the universe — a prestressed structure held together by persistent dynamical primitives.

---

4. Space as Osmotic Pressure

4.1 Osmotic Pressure in Biology

In the biological framework, GAGs and proteoglycans generate osmotic swelling pressure — a distributed expansive force.

4.2 Space as Expansive Medium

Within this framework, space is interpreted as an expansive medium analogous to osmotic pressure:

Property	Interpretation
Cosmic expansion	The “osmotic pressure” of space — it expands because it is pressurised
Cosmic acceleration	The pressure is not constant — it is increasing (dark energy)
Structure formation	The metronomes constrain the expansion into coherent structures

Within this framework, space is not empty. It is an active, pressurised medium. Its expansion is the “osmotic pressure” of the universe.

5. Dark Energy as WHC-Water Discrepancy

5.1 WHC-Water Discrepancy in Biology

In the biological framework, WHC-water discrepancy is the difference between theoretical water-holding capacity and actual water content — the “water held back” by collagen.

5.2 The Cosmic Discrepancy

In the cosmological framework, the cosmological constant (Λ) can be interpreted as the cosmic WHC-water discrepancy:

Observation	Interpretation
Matter-only expansion would decelerate	The “theoretical maximum” expansion
Observed expansion is accelerating	The “actual” expansion
The gap is filled by dark energy	The cosmic “water held back”

In ΛCDM, the observed expansion history requires a cosmological constant ($\Omega_\Lambda \approx 0.68$). Without it, the universe would decelerate. The gap between these two scenarios is precisely the WHC-water discrepancy at cosmic scale.

5.3 Falsification Condition

The WHC-Λ interpretation would be falsified if:

1. Dark energy were shown to have a dynamical nature fundamentally different from a cosmological constant (e.g., evolving dark energy with equation of state $w \neq$

-1)
2. The expansion history were found to be consistent with matter-only dynamics without Λ
3. The cosmological constant were derived from a mechanism that explicitly rules out the “max-minus-actual” interpretation

Note on Condition 1: This is not a remote hypothetical — it is currently the subject of live observational tension. DESI DR2 (2025), combined with supernova and CMB priors, shows a continuing preference for an evolving equation of state, with independent DES analysis reporting roughly 3.2σ preference for evolving dark energy over ΛCDM. However, a May 2026 systematics study (Afroz & Mukherjee) suggests part of the signal may trace to a cosmic-distance-duality mismatch between the BAO and supernova datasets rather than genuine dark-energy evolution. The field is currently split between “real signal” and “systematic artifact” readings. This is precisely the kind of live tension that a falsifiable heuristic should engage with — it shows that the condition is genuinely live, not a distant hypothetical.

5.4 Limitations

Issue	Address
Λ is a fitted parameter	It is not derived from a “max-minus-actual” calculation
No standard formalism equates Λ to a discrepancy	This is an interpretation, not a mathematical derivation
The framework is descriptive, not predictive	It describes what ΛCDM already describes

The interpretation is coherent but not yet operational. It is offered as a generative heuristic, not a replacement for ΛCDM.

---

6. Dynamics at Cosmic Scale

6.1 What is κ at Cosmic Scale?

In biology, κ is the rate at which a system returns to its dynamical trajectory after perturbation. At cosmic scale, κ is the rate at which the universe "corrects" deviations:

Candidate	Interpretation
Inflation	A period of rapid correction — a phase transition
Cosmic acceleration	The universe's ongoing "correction" toward a de Sitter attractor
Hubble rate approach to H_∞	The rate at which the universe approaches its de Sitter state

κ is defined as the rate of recovery toward the system's dynamical trajectory. The universe has no equilibrium state, but it has a dynamical trajectory — the expansion history. The approach to a de Sitter fixed point is a dissipative process in the horizon-thermodynamic sense.

Currently, no standard cosmological parameter explicitly measures κ. The concept is coherent but not yet operational.

Note on formalization: Ultimately, κ should be expressed as the largest negative eigenvalue of the linearized dynamics around an attractor. This would give κ the same mathematical meaning across all domains — cells, brains, AI, and cosmology would compute κ differently, but the mathematics would be identical. This is an open research question.

6.2 What is B at Cosmic Scale?

In biology, B is the energy barrier required to shift a system from one attractor state to another. At cosmic scale, B maps to:

Candidate	Interpretation
Vacuum stability	The depth of the vacuum basin
False vacuum lifetime	The time until a vacuum decay event
Inflationary potential barriers	The barriers between inflationary states

These actually resemble basin depth. Fundamental constants — which show no sign of variation over cosmic time — imply a very deep basin, but B itself is not the constants; it is the stability of the attractor landscape in which they are embedded.

Observation	Interpretation
Constants do not vary	$\Delta\alpha/\alpha < 10^{-17}$ per year — the basin is deep
Laws are stable	The universe resists perturbation
No observed transitions	No evidence of the universe “shifting” between attractors

B is inferred from constant stability, not measured directly.

6.3 The Universe as a Dissipative Attractor

Within this framework, the universe is interpreted as a **dissipative attractor in the horizon-thermodynamic sense**. De Sitter horizons exhibit Gibbons–Hawking temperature and horizon entropy, indicating entropy production without external energy input. The approach to a de Sitter fixed point is a genuinely dissipative process — phase-space contraction occurs through horizon thermodynamics.

This resolves the apparent tension: The universe has no external energy source, but it is not conservative in the attractor-theoretic sense. It is dissipative internally, through horizon dynamics.

Conservative systems — in the strict dynamical-systems sense — do not have attractors. The universe, approached as a de Sitter fixed point with horizon thermodynamics, is dissipative in the relevant sense. This is consistent with the framework's definition of κ as a recovery rate toward an attractor.

---

7. Observational Evidence

7.1 Cosmic Web as Rebar Constraints

Observations of large-scale structure show a cosmic web of galaxies arranged in filaments, sheets, and voids. This pattern is precisely what one would expect if massive particles (metronomes) constrained expansion:

Observation	Interpretation
Filaments	"Strands" under tension
Voids	Regions of low density, expanding freely
Clusters	Nodes where filaments intersect

The cosmic web is the "tissue" of the universe — a prestressed structure.

7.2 Expansion and ΛCDM

The expansion history of the universe is well described by ΛCDM. The "gap" between matter-only deceleration and observed acceleration is filled by dark energy:

Observation	Interpretation
$\Omega_\Lambda \approx 0.68$	Dark energy comprises ~68% of the universe’s energy density
Λ fits the data	The model matches CMB, BAO, and supernovae observations

The WHC-water discrepancy interpretation is consistent with ΛCDM.

7.3 Fundamental Constants and Basin Depth

Fundamental constants show no sign of variation over cosmic time. Dimensionless combinations containing c (e.g., the fine-structure constant α) are tightly constrained:

Constant	Variation Limit
α (fine-structure)	$<10^{-17}$ per year
G (gravitational)	$<10^{-12}$ per year
Lorentz invariance	Constrained by observations of high-energy photons from gamma-ray bursts

This implies a very deep basin — the constants are stable and resist perturbation.

---

8. Taoist Mapping

8.1 The Tao as Constraint Field

The Tao is described as the underlying order of all things — the “Way.” In the framework, this corresponds to the **constraint field** (attractor landscape), not the prestressed system itself.

Taoist Concept	Framework Mapping
The Tao	The constraint field — the underlying order

Taoist Concept	Framework Mapping
The universe	The prestressed system — the expression of the Tao

8.2 Wu Wei and High κ

Wu wei means "non-action" or "effortless action" — responding with natural ease rather than forcing. This corresponds structurally to high κ:

Wu Wei	High κ
Flowing with the Tao	Correcting errors smoothly
Not forcing	Rapid return to equilibrium
Natural harmony	System-level corrigibility

Caution: Wu wei is a felt quality of action as much as κ is a measured rate. The mapping is structural rather than literal — both describe a system that responds appropriately to perturbation without resistance.

8.3 Ziran and R (Reality Alignment)

Ziran means "naturalness" — being as one is, without external coercion. This is a **structural analogy**, not an equivalence:

Ziran	R (Reality Alignment)
Being what it is	Models correspond to reality
Without force	No external coercion
True to nature	Alignment with the Tao

Caution: Ziran is closer to spontaneous self-so-ness than to epistemic accuracy. Reality alignment (R) concerns how well a model corresponds to the external world. These overlap but are not identical. The mapping is structural, not causal.

8.4 Te (Virtue) and B (Basin Depth)

Te (virtue) in Taoist thought refers to the integrity and stability of a being's character — its capacity to maintain coherence without forcing. This structurally corresponds to basin depth (B): the ability to resist perturbation while maintaining identity.

Te (Virtue)	B (Basin Depth)
Maintains integrity	Resists perturbation
Does not force	Holds identity
Stable character	Deep attractor basin

The mapping is structural, not causal. B at the cosmic scale (stability of constants) and B at the personal scale (stability of character) are distinct phenomena that share the same dynamical form.

8.5 The Taoist Sage and the Attractor Ideal

Taoist Concept	Framework Translation
Wu wei	High κ — flow with the Tao
Ziran	High R — align with reality (structural analogy)
Te (virtue)	High B — maintain integrity
The sage	High κ + high B + high R

---

9. What This Paper Does Not Claim

This paper does not claim:

- The universe is alive
- The universe is conscious

- The universe has a mind
- The framework replaces ΛCDM
- The framework is a theory of everything
- The framework generates novel predictions (currently descriptive)
- The universe is conservative in the attractor-theoretic sense
- Mathematical equivalence between biological and cosmological systems

---

10. Limitations

Limitation	Address
Λ is a fitted parameter	It is not derived from a "max-minus-actual" calculation
κ is not operational at cosmic scale	No standard cosmological parameter measures "recovery toward dynamical trajectory"
B is not operational at cosmic scale	No direct measurement of basin depth exists
The framework is descriptive, not predictive	It describes what ΛCDM already describes
No new testable predictions	The framework must develop falsifiable predictions to move beyond heuristic status
The framework's universality is an empirical hypothesis	It must be tested across domains

These limitations are acknowledged. The paper is offered as a **generative heuristic** — a cross-domain unification and a vocabulary for seeing connections, not a replacement for ΛCDM.

11. Open Research Questions

Question 0: Are κ, B, C, and R scale-invariant?

Can κ, B, C, and R be defined consistently across scales — from cells to societies to the cosmos? If κ_{cell}, κ_{brain}, $\kappa_{society}$, and $\kappa_{universe}$ are fundamentally different, the framework fragments. If they can all be derived from one equation, the framework is unified.

Falsification: If the variables cannot be defined consistently across scales, the framework is not universal.

Question 0.1: What are the units of κ, B, C, and R in each domain?

κ sometimes equals 1/time, sometimes appears dimensionless, sometimes is a qualitative property. Universal frameworks require dimensional consistency or explicit normalization.

Falsification: If the variables cannot be given consistent units, the framework is not operational.

Question 0.2: Can a domain-independent state equation be written?

Can the framework be expressed as: $\frac{dX}{dt}=f(\kappa,B,C,R,X,E)$

where X is the system state, E represents external perturbations, and κ, B, C, and R are parameters or functions with clearly defined roles?

The framework does not need a universal closed-form equation for every domain. But it does need to specify the functional role of each variable:

- Does increasing B always reduce transition probability between attractors?
- Does increasing κ always increase recovery rate after perturbation?
- Does C alter coupling strength between subsystems?
- Does R change how internal models update in response to evidence?

Falsification: If each domain requires entirely different equations, the framework is a taxonomy, not a unified theory.

Question 0.3: Does κ emerge from interaction topology?

Can κ be derived from the structure of the interaction manifold, or is it primitive? If derived, this would be a major theoretical advance.

Falsification: If κ cannot be derived from more fundamental properties, it remains primitive.

Question 0.4: Is B conserved or variable?

Does B increase with age? Decrease? Oscillate? Can B be measured directly? These are empirical questions.

Falsification: If B cannot be measured or shows no systematic behavior, the concept is not operational.

Question 0.5: How do κ, B, C, and R couple?

Are κ, B, C, and R independent, or do they interact? Can R increase without increasing κ? Can high B produce high C? Can

C suppress κ? These relationships should be modeled explicitly.

Falsification: If the variables show no systematic relationships, the framework lacks predictive power.

---

12. Conclusion

The universe can be interpreted as a prestressed system:

Element	Role
Three metronomes (e^-, p^+, ν)	Persistent dynamical primitives — “rebar”
Space	Osmotic pressure — expanding medium
Cosmological constant (Λ)	WHC-water discrepancy — the gap between theory and observation

The framework does not claim that the universe is alive or conscious. It claims that the universe is a dissipative system that persists under perturbation — and within the attractor framework, that is the defining characteristic of intelligence at its most basic level.

The Taoist mapping is structurally coherent: the Tao is the constraint field, wu wei is high κ (structural analogy), ziran is R (structural analogy), and te is B.

The framework is offered as a generative hypothesis, not a replacement for ΛCDM. Its value lies in its cross-domain unification and its ability to generate new questions — not in its predictive power, which remains to be established.

The next step is not additional analogies. It is mathematical formalization: can the framework’s variables be expressed in a domain-independent state equation? Can κ, B, C, and R be given consistent units across scales? Can the framework generate at

least one novel, falsifiable prediction that competing frameworks would not naturally generate? These are the questions that will determine whether the framework remains a heuristic or becomes a scientific theory.

References

- Galida, R. (2026a). “Intelligence is the Primitive: Consciousness as a Second-Order Regulator on a Dissipative Substrate.” *Fantasy Attractor.*
- Galida, R. (2026b). “The Attractor Framework as a Formal Mapping of Taoist Dynamics.” *Fantasy Attractor.*
- Galida, R. (2026c). “The Pre-tensioned Body: A Hypothesis Paper Grounding the Attractor Framework in ECM Mechanics.” *Fantasy Attractor.*
- Galida, R. (2026d). “Non-Physical Claims Are Fantasy Attractors: Why Unverifiable Realms Cannot Be Empirically Distinguished from Nonexistence.” *Fantasy Attractor.*
- Planck Collaboration (2020). “Planck 2018 results. VI. Cosmological parameters.” *Astronomy & Astrophysics*, 641, A6.
- Riess, A.G., et al. (1998). “Observational evidence from supernovae for an accelerating universe and a cosmological constant.” *The Astronomical Journal*, 116(3), 1009.
- Perlmutter, S., et al. (1999). “Measurements of Ω and Λ from 42 high-redshift supernovae.” *The Astrophysical Journal*, 517(2), 565.
- Gibbons, G.W., & Hawking, S.W. (1977). “Cosmological event horizons, thermodynamics, and particle creation.” *Physical Review D*, 15(10), 2738.

Suggested citation: Galida, R. S. (2026). The Universe as a Prestressed System: A Taoist Cosmology. *Fantasy Attractor*.

The West and the East: A Research Protocol for Civilizational Attractor Dynamics

Robert Galida
June 2026
[A] (Application)

Abstract

The attractor framework provides a vocabulary for diagnosing the dynamical properties of systems—their error correction capacity (κ), their perturbation resistance (B), their coordination capacity (C), and their reality alignment (R). This paper proposes a research protocol for applying that vocabulary to institutional and civilizational scales. It introduces a four-dimensional framework distinguishing these variables, operationalizes them using candidate observables—policy correction rates, scientific retraction rates, institutional durability, identity persistence, institutional trust, and scientific acceptance—and outlines a research protocol for testing hypotheses about civilizational

dynamics. The paper applies the framework provisionally to case studies, including the Meiji Restoration, the Genesis 1 flat-earth cosmology, and Western responses to Asia's rise. It concludes that the framework generates testable predictions about institutional and civilizational adaptation, but that all claims are provisional pending empirical validation.

All claims are hypotheses, not conclusions. The framework is applied heuristically, not diagnostically.

---

1. Introduction

The attractor framework has been applied to physics, biology, cognition, and AI. This paper extends it to civilizational dynamics. It does not claim that civilizations are organisms or that the framework has been validated at this scale. It proposes a research protocol and generates hypotheses for empirical testing.

The central hypothesis is:

> *Western and East Asian civilizational traditions may occupy different attractor basins, with the West potentially exhibiting lower error correction capacity (κ) and higher perturbation resistance (B) than Taoist-Confucian-influenced East Asian traditions.*

This is a hypothesis, not a conclusion. It requires operationalization, measurement, and falsification.

A note on the framework's physicalist commitment: The attractor framework adopts a physicalist ontology: to be real is to be able to interact, and to interact is to share at least one interaction channel (energy, momentum, gauge charge, spacetime, or any measurable coupling). Claims that define themselves as having no such channels are fantasy attractors: structurally sealed against correction by permanent non-verifiability (see Galida, 2026f). This paper extends that diagnostic logic from individual beliefs to civilizational self-images—but always as a hypothesis, never as an established conclusion.

---

2. The Framework Variables: A Four-Dimensional State Space

The attractor framework's normative ideal is **high κ + high B + high C + high R**—a system that corrects errors efficiently, resists perturbation, coordinates collective action, and aligns with reality.

Variable	Definition	High Value	Low Value
κ (error correction capacity)	The rate at which a system detects and corrects errors in its models	Learns from mistakes, updates beliefs	Repeats errors, resists updating
B (perturbation resistance)	The energy barrier required to induce a durable state transition	Stable, coherent, retains identity	Shallow, unstable, easily perturbed
C (coordination capacity)	The ability of a system to coordinate collective action	Cohesive, effective	Fragmented, ineffective

Variable	Definition	High Value	Low Value
R (reality alignment)	The degree to which a system's models correspond to empirical reality	Accurate models	Delusional models

Crucially, κ is not change rate. It is error correction rate. A system can change constantly and still be irrational (high change, low κ). A system can appear conservative and still possess extremely high κ because correction occurs when evidence accumulates (low change rate, high κ).

The Four Outcomes

Combination	κ	B	Outcome	Examples
Stable adaptive	High	High	The ideal—corrects errors, maintains coherence	Scientific communities, healthy individuals, functioning democracies
Brittle adaptive	High	Low	Corrects errors but unstable—no memory, no coherence	Chaotic organizations, fad-followers
Stable rigid	Low	High	Resists correction—dogmatic, sealed	Fantasy attractors, fundamentalism
Fragile rigid	Low	Low	Unstable and unresponsive	Failed states, collapsed institutions

The Fantasy Attractor Defined

A fantasy attractor is not simply a low-κ system. It is:

> ***A system with low R (reality alignment) combined with mechanisms that prevent R from increasing.***

This definition is more powerful than the earlier “low κ + high B” formulation because it explains why some low-κ systems are not fantasy attractors (e.g., a conservative scientific community that is low-κ in the short term but high-R in the long term). It also explains why some high-κ systems are fantasy attractors (e.g., conspiracy communities that change constantly but never converge on reality).

---

3. Operationalizing κ, B, C, and R

3.1 Candidate Proxies for κ (Error Correction Capacity)

Proxy	Description	Data Source
Policy correction rate	How quickly does a society correct failed policies?	Comparative Agendas Project, legislative archives
Scientific retraction rate	How readily does a field retract false findings?	Retraction databases, replication studies
Error detection capacity	How effectively does a system identify its own errors?	Institutional review mechanisms, ombudsman data

Falsification: If societies scoring high on these proxies do not show improved outcomes over time, the mapping fails.

3.2 Candidate Proxies for B (Perturbation

Resistance)

Proxy	Description	Data Source
Institutional durability	How long do institutions persist under pressure?	Historical duration data, institutional survival rates
Constitutional stability	How resistant is the foundational framework to change?	Constitutional amendment difficulty, legal entrenchment
Identity persistence	How stable is collective identity over time?	National identity surveys, historical continuity measures

Falsification: If systems with high values on these indicators nonetheless show high adaptability without collapse, the mapping needs refinement.

3.3 Candidate Proxies for C (Coordination Capacity)

Proxy	Description	Data Source
Institutional trust	Public confidence in institutions	World Values Survey, trust indices
Collective action capacity	Ability to mobilize resources	State capacity indices, tax-to-GDP ratios
Social cohesion	Degree of social integration	Social capital indices, inequality measures

3.4 Candidate Proxies for R (Reality

Alignment)

Proxy	Description	Data Source
Scientific acceptance	Public acceptance of scientific consensus	Evolution acceptance, climate change belief
Historical accuracy	Acknowledgment of historical facts	Content analysis of textbooks
Empirical openness	Willingness to revise beliefs in light of evidence	Survey measures of epistemic openness
Predictive accuracy	How well do models predict outcomes?	Forecast accuracy, planning effectiveness

3.5 Testing the Latent Structure

The framework assumes that these indicators load onto shared latent variables (κ, B, C, R). This assumption must be tested using:

- **Exploratory factor analysis** to see whether the indicators group as predicted
- **Confirmatory factor analysis** to test the hypothesized factor structure
- **Cross-validation** across different cultural contexts

Falsification: If the indicators do not load onto the predicted latent variables, the framework's operationalization fails.

---

4. Institutions First, Civilizations Second

"The West" and "The East" are not coherent dynamical entities. Medieval Spain, Puritan New England, contemporary Sweden, and Renaissance Florence may have radically different κ, B, C, and R values. Likewise, Tokugawa Japan, Maoist China, Singapore, and contemporary South Korea are not obviously members of one attractor.

Treatment: The framework is better applied to **institutions** (universities, bureaucracies, religions, states, scientific communities) than to civilizations as wholes. Case studies should specify time periods and institutional contexts.

Institution	κ	B	C	R
Imperial examination bureaucracy	?	?	?	?
Catholic Church (1200)	?	?	?	?
Royal Society (1700)	?	?	?	?
CCP bureaucracy (1985)	?	?	?	?
Silicon Valley startup ecosystem	?	?	?	?

These are actual dynamical systems. Civilizations are aggregates. The framework becomes more falsifiable when applied to institutions first.

---

5. Hypotheses for Empirical Testing

5.1 The West/East Hypothesis (Institutional Form)

Hypothesis: Taoist-Confucian-influenced institutions exhibit higher κ and higher R than Western institutions.

Test: Compare institutions (universities, bureaucracies, scientific communities) across cultural contexts.

Falsification: If Western institutions show higher κ or higher R, the hypothesis fails.

5.2 The Meiji Challenge Hypothesis

Competing hypothesis: High κ emerges from elite willingness to revise institutional models under external pressure, rather than from cultural tradition.

Test: Compare Meiji Japan with Peter the Great's Russia, Atatürk's Turkey, and Deng's China.

Falsification: If high κ episodes occur without external pressure, the competing hypothesis fails.

5.3 The Genesis Hypothesis

Hypothesis: Foundational narratives become identity-protected when tied to group cohesion.

Test: Compare response to evidence across different foundational narratives (Genesis, Marxism, nationalism, revolutionary myths).

Falsification: If some foundational narratives show high κ and high R, the hypothesis needs refinement.

5.4 The Social Enforcement Hypothesis

Hypothesis: The cost of rejecting a dominant attractor—exclusion, censure, hostility—is high enough to prevent most people from leaving the basin.

Test: Qualitative and quantitative studies of independent researchers, religious doubters, and political dissenters.

Falsification: If the social cost of rejection is low, the hypothesis fails.

5.5 The Escape Hypothesis

Hypothesis: Deep attractors often require unusually large perturbations to reorganize.

Test: Historical analysis of civilizational transformations (Roman Empire, Mayan civilization, Japan’s Meiji Restoration, China’s Reform and Opening).

Falsification: If civilizations escape deep attractors without large perturbations, the hypothesis fails.

---

6. Case Studies (Provisional)

6.1 The Meiji Restoration: High κ Under External Pressure

Japan’s Meiji Restoration (1868) is a case study in high κ: a deliberate, rapid shift toward pragmatism and adoption of foreign ideas. However, Meiji was not particularly Taoist. It was hyper-modernizing, militarizing, industrializing, and centralizing.

Competing hypothesis: High κ emerged from existential threat (Perry’s arrival) combined with elite flexibility. This mechanism appears elsewhere: Peter the Great’s Russia, Atatürk’s Turkey, Deng’s China.

Implication: Taoism may be secondary to elite flexibility under external pressure.

6.2 The West's Response to Asia's Rise

The West's response to Asia's rise—demonization, containment, resistance to learning—is consistent with fantasy attractor dynamics. However, this is a hypothesis, not a conclusion.

Counterexample: The West has also adopted Asian technologies and business practices. This suggests that κ may be higher in some domains (technology) than others (identity).

6.3 Genesis 1 as a Case Study

The West's refusal to acknowledge Genesis 1's flat-earth cosmology is a case study in identity-protective sealing. However, it is one example among many.

Broader framing: Foundational narratives—whether religious, national, revolutionary, or ideological—become identity-protected when tied to group cohesion. Genesis is one example. Marxism, nationalism, revolutionary myths, imperial myths, and anti-colonial myths are others.

---

7. How This Maps to Taoism

Taoist Concept	Attractor Interpretation
Wu wei (non-action)	High κ—respond appropriately to the situation
Ziran (naturalness)	High R—align with the way things actually are
The Tao	The constraint field—the attractor landscape itself
Te (virtue)	High B—maintain integrity while flowing
The sage	High κ + high B + high R—the ideal

A crucial clarification: Taoism is treated as an **inspiration**

for the model, not as **evidence that the model is true**. The empirical version is:

> *Taoism predicts certain dynamical properties. We can test whether systems influenced by Taoist ideas actually exhibit those properties.*

This preserves falsifiability and avoids circularity.

---

8. What This Paper Does Not Claim

Claim	Not Claimed
The West is definitively low-κ	□
The East is definitively high-κ	□
Genesis 1 is the sole sealing mechanism	□
Taoism is evidence for the framework	□
All Western institutions are rigid	□
All Eastern institutions are adaptive	□
The framework has been validated at civilizational scale	□
Civilizations are organisms	□
High change rate = high κ	□

---

9. Research Protocol and Methodology

9.1 Data Sources

- Political freedom indices (Freedom House, Polity)
- Innovation and education indices (Global Innovation Index, PISA)
- Survey data on belief systems (World Values Survey)
- Historical texts and news archives for qualitative analysis

9.2 Variables and Measurement

Variable	Proxy	Measurement
κ (error correction)	Policy correction rate	Count failed policies corrected
κ (error correction)	Scientific retraction rate	Retraction databases
κ (error correction)	Error detection capacity	Institutional review mechanisms
B (perturbation resistance)	Institutional durability	Historical duration data
B (perturbation resistance)	Constitutional stability	Amendment difficulty
B (perturbation resistance)	Identity persistence	Historical continuity measures
C	Institutional trust	World Values Survey
C	Collective action capacity	State capacity indices
R	Scientific acceptance	Evolution acceptance, climate change belief
R	Historical accuracy	Content analysis of textbooks
R	Predictive accuracy	Forecast accuracy

9.3 Statistical Analysis

- **Exploratory factor analysis** to see whether indicators group as predicted
- **Confirmatory factor analysis** to test the hypothesized factor structure
- **Cross-validation** across different cultural contexts
- **Longitudinal analysis** to track changes over time

9.4 Falsification Criteria

For each hypothesis, define outcomes that would disprove it. For example, if Western institutions score higher on error correction capacity than Eastern ones, reject the corresponding hypothesis.

---

10. Conclusion

The attractor framework generates testable hypotheses about institutional and civilizational dynamics. The central hypothesis is that Western and East Asian civilizational traditions may occupy different attractor basins, with the West potentially exhibiting lower error correction capacity (κ) and higher perturbation resistance (B) than Taoist-Confucian-influenced East Asian traditions.

Crucially, the framework's normative ideal is high κ + high B + high C + high R. The fantasy attractor is not simply low κ. It is low R combined with mechanisms that prevent R from increasing.

The research protocol outlined in this paper provides a path for empirical testing. Until that testing is complete, all claims are provisional.

The paper does not claim that the West is definitively a fantasy attractor. It claims that the framework generates the hypothesis that the West may exhibit characteristics consistent with a fantasy attractor—and that this hypothesis is testable.

References

- Galida, R. (2026a). “Intelligence is the Primitive: Consciousness as a Second-Order Regulator on a Dissipative Substrate.” *Fantasy Attractor.*
- Galida, R. (2026b). “The Attractor Framework as a Formal Mapping of Taoist Dynamics.” *Fantasy Attractor.*
- Galida, R. (2026c). “The Cosmology of Genesis: A Philological and Exegetical Examination of the Flat Earth, Solid Dome, and Cosmic Ocean in the Hebrew Bible.” *Fantasy Attractor.*
- Galida, R. (2026d). “The Pre-tensioned Body: A Hypothesis Paper Grounding the Attractor Framework in ECM Mechanics.” *Fantasy Attractor.*
- Galida, R. (2026e). “Religions and Philosophies as Attractor Landscapes: A Comparative Analysis.” *Fantasy Attractor.*
- Galida, R. (2026f). “Non-Physical Claims Are Fantasy Attractors: Why Unverifiable Realms Cannot Be Empirically Distinguished from Nonexistence.” *Fantasy Attractor.*
- Gelfand, M.J., et al. (2011). “Differences Between Tight and Loose Cultures: A 33-Nation Study.” *Science* 332(6033):1100–1104.

Suggested citation: Galida, R. S. (2026). The West and the

East: A Research Protocol for Civilizational Attractor Dynamics. *Fantasy Attractor*.