A General Theory of Cohesion

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Abstract

I present a general system of equations for measuring cohesion γ; a scale invariant measure of dynamic, boundary constrained systems, maintained by energy management processes, made up of components which have unique action vectors, and are influenced by other system boundaries. This boundary centric framework defines system viability through measurable energy tradeoff functions: boundary maintenance, predictive efficiency, component action vector alignment and system:system interaction costs. Each system S is defined as a boundary function $B(S)[\mathcal{A}]$, where $\mathcal{A}$ is the internal action vector field acting upon the boundary. Cohesion γ is computed as a scalar energy balance describing whether the system can maintain boundary integrity across time given internal coordination costs, and multi-system interactions. Interaction between systems is modeled as a differential constraint function $\Psi(B_i, B_j)$ that quantifies the added cost of exploration, exploitation, or maintenance imposed by one system's boundary on another. This framework enables cross-domain modeling of system emergence, persistence, and collapse by unifying resource dynamics, environmental feedback, and inter-system pressure within a single formal language. Cohesion becomes a computable outcome of dynamic boundary conditions, not a metaphysical or statistical assumption. The result is a modular, scale-invariant theory for analyzing coherent structure and relational dynamics in complex environments.

1 Introduction

This General Theory of Cohesion proposes a universal system of equations that models the viability of any System S as a function of its boundary dynamics, which are in-turn a function of internal energy management and component action vector alignment. Systems are defined as boundary functions $B(S)$ maintained by internal action vectors $\mathcal{A}$ and evaluated based on their energetic stability, predictive accuracy, and interaction with surrounding systems.

The theory is scale-invariant for any object or system composed of elements constrained by the Pauli Exclusion Principle. Cohesion is measured by whether the boundary can be sustained given the system's stored energy, alignment efficiency, and expected reward predictions for balancing net energy costs across multiple system interactions.

Practitioners must define:

- The structure, dimensionality and state of the system boundary
- The internal action vector field that sustains the boundary
- The localized boundary interaction pressure from other system boundaries

The scalar cohesion function $\gamma(B(S))$ measures whether a system can maintain its boundary across time. It incorporates:

1. Boundary maintenance cost, including alignment inefficiencies
2. Predicted energy balance for multiple system interactions
3. Forward time horizon over which viability is evaluated

Interactions between systems are defined by a constraint-based function $\Psi(B(S_i), B(S_j))$, which quantifies the differential cost imposed on each system by the presence of the other. These interactions determine whether systems exhibit absorptive (cooperative), ablative (competitive), or ambivalent (neutral) relationships.

Cohesion transitions occur when systems shift between viable and non-viable states. These transitions are governed by energetic thresholds and predictive failures. Systems with greater internal coherence and lower interaction pressure are more resilient to environmental change.

Key principles of the theory include:

- System persistence as the zeroith-goal for any system, with energy management and mutli-system prediction efficiency as the bottlenecks determining system stability and longevity
- Internal component action vector misalignment reduces resources allocated toward boundary functions
- Boundary dynamics encode all relevant system-environment relationships

- Multi-system environments are emergent from the constraint web Ψ across boundaries

This framework provides a generalizable mathematical foundation for modeling the emergence, maintenance, and collapse of complex systems without relying on metaphysical assumptions or statistical abstractions. It applies across domains by treating cohesion as the computable result of active boundary management under finite resource constraints.

2 The General Cohesion Function

Cohesion is defined through its measurable energetic and informational components at the system boundary. Each system S_i is defined by its boundary $B(S_i)$ and the internal action vectors $\mathcal{A}_i$ which act upon it. The internal stability of the system is determined by whether the boundary can be maintained over time given internal resource constraints and environmental pressure.

$$\gamma(B(S_i)) = \left[\frac{B_t^*(B(S_i))}{\kappa_t}\right] + \eta \cdot U(\hat{R}_t) + \frac{H(S_{t+1}) - H(S_{t+1} \mid \hat{S}_{t+1})}{g(\mu, \lambda_t, \tilde{M}_t)} + \tau$$

where:

- $B_t^*(B(S_i)) = B_t + C_{\text{align}}(t)$ is the total boundary cost, composed of:
  - B_t: the energetic cost of maintaining the structural or symbolic boundary $\partial(S_i)$, given its complexity, interaction pressure Φ_{ij}, and boundary state $B_c(t)$.
  - $C_{\text{align}}(t) = \sum_{i=1}^{n} w_i \|\vec{a}_i(t) - \hat{A}_S(t)\|$: the cumulative internal misalignment cost, where w_i is the weight (influence, memory, or inertia) of each component, $\vec{a}_i(t)$ is the component's action vector, and $\hat{A}_S(t)$ is the system consensus vector. This can be thought of as the amount of effort it takes to keep everything aligned.
- $\kappa_t = \dfrac{E_{\text{stored}}(t)}{\alpha \cdot |\partial(S_i)| + \beta \cdot E_{\text{explore}}(t)}$ is the adaptive stability margin, representing how much stored energy is available to buffer against collapse.
- $E_{\text{stored}}(t) = \int_{t-\Delta t}^{t} [E_{\text{gain}}(t') - B_t^*(t')]\, dt'$ is the net stored energy over a rolling window Δt.
- $\eta \cdot U(\hat{R}_t)$ is the predicted usable energy from the environment, where:
  - η is the exploitability coefficient of predicted resources.
  - $\hat{R}_t = \Pi(S_t, S_{t-1}, ..., S_{t-\mu})$ is the system's prediction of the resource field.
  - $U(\cdot)$ maps predicted resources to usable internal energy.

- $\frac{H(S_{t+1}) - H(S_{t+1} | \hat{S}_{t+1})}{g(\mu, \lambda_t, \tilde{M}_t)}$ is the prediction efficiency:
  - $H(S_{t+1})$: entropy of the true next state.
  - $H(S_{t+1} \mid \hat{S}_{t+1})$: entropy conditional on the system's prediction.
  - $g(\mu, \lambda_t, \tilde{M}_t)$: cost function for predictive capacity based on memory depth μ, attention bandwidth λ_t, and motion potential $\tilde{M}_t$.
- τ is the forward time horizon over which the system attempts to maintain cohesion.

Cohesion $\gamma(B(S_i))$ is a scalar expression of viability at time t. If it falls below a domain-defined critical threshold $\gamma_{\min}$, the system is unable to maintain coherence and undergoes dissolution, fragmentation, or absorption depending on environmental pressures and boundary state.

3 Defining a System and Boundary State

In this boundary focused framework, a system S_i is not defined as a static collection of components, but as a boundary function $B(S_i)$ whose continued integrity is actively sustained by an internal set of action vectors $\mathcal{A}_i$. The system is only recognizable to other systems and the environment by its boundary, and only viable if that boundary remains energetically coherent over time.

$$S_i := B(S_i)[\mathcal{A}_i]$$

where:

- $B(S_i)$ is the boundary function $\partial(S_i)$, which defines the edge of the system and filters all system-environment interactions.
- $\mathcal{A}_i = \{\vec{a}_1(t), \vec{a}_2(t), ..., \vec{a}_n(t)\}$ is the internal set of component action vectors that sustain or alter the boundary.

The boundary mediates all interaction with the external world and serves as the only interface through which cohesion, resource uptake, alignment, and prediction are enacted. If the boundary dissolves, the system ceases to function or be recognizable.

3.1 Boundary Structure and Identity

The boundary $B(S)$ is a measurable construct: physical, symbolic, chemical, or computational, that acts as both effector and filter. It determines what is internal to the system and what remains external. The complexity and dimensionality of the boundary affect its energetic cost and its filtering capabilities.

Formally:

$$\partial(S_i) \in M \quad \text{where } M \text{ is the space of measurable interfaces}$$

The geometry, bonding configuration, and permeability of $\partial(S_i)$ determine its maintenance cost B_t and its vulnerability to environmental pressure Φ_{ij}.

3.2 Boundary Hypothesis: Gradient-Sustaining Aligned Subset

We define the boundary as a dynamically selected, specialized subset of components within the system, whose action vectors align to maintain a pressure differential across the system-environment interface:

$$\partial(S_n) = \left\{ x_i \in S_n \;\middle|\; \exists\, \hat{a} \in \mathbb{R}^m \text{ such that } \arg\min_{x_i} \left\| \sum_{i=1}^{n_b} w_i \vec{a}_i - \hat{a} \right\| \text{ and } \nabla \Phi_{ij}(\partial(S_n)) \geq \varepsilon \right\}$$

Where:

- $x_i \in S_n$: Components that may form part of the system boundary.
- n_b: Number of components that form the effective boundary at time t.
- $\vec{a}_i$: Action vector of component x_i.
- w_i: Weight of the component's contribution to vector global alignment (eg. variation from components adjacency field and degree to which field aligns or not with component)
- $\hat{a}$: Idealized vector field maintaining a stable pressure differential.
- $\nabla\Phi_{ij}(\partial(S_n))$: Pressure gradient across boundary between system S_n and adjacent system or environment.
- ε: Threshold to trigger boundary state change

This hypothesis suggests that the boundary is dynamically emergent from the alignment of internal agents that best maintain interaction gradients, not statically imposed.

3.3 Internal Action Vector Alignment Cost

Internal coherence requires that the action vectors $\vec{a}_i(t)$ remain aligned to the system's desired direction or functional consensus $\hat{A}_S(t)$. Misalignment incurs an energetic cost that reduces the ability to use $E_{\text{available}}$ for boundary functions.

$$C_{\text{align}}(t) = \sum_{i=1}^{n} w_i \left\| \vec{a}_i(t) - \hat{A}_S(t) \right\|$$

Where:

- $\vec{a}_i(t)$: Time-indexed action vector of component i.
- $\hat{A}_S(t)$: Consensus or optimal system action vector at time t.
- w_i: Weighting factor for influence, memory encoding, or structural inertia.

This cost is nonzero whenever internal action vectors diverge from the system's target trajectory or stability goal. Alignment gradients can be maintained through memory, environmental scaffolding, authority, or feedback mechanisms.

3.4 Boundary State Types

The system boundary can exist in several states, based on energy availability and interaction pressure. These states represent different strategies for managing external interaction and structural integrity and are dynamic, transitioning between states in response to or in anticipation of internal energy and external interaction gradients.

- **Ablative**: S_i dissolves or consumes S_j by degrading its boundary.

  Examples: Carnivorous predation, conquest, digestion.

- **Absorptive**: S_j is integrated into S_i without destroying either boundary.

  Examples: Endosymbiosis, corporate merger, parasitism.

- **Ambivalent**: Both systems retain boundaries; no net interaction pressure $\Phi_{ij} = 0$.

3.5 Boundary State Transition Function $B_c(t)$

The transition between boundary states is modeled as a function of internal stored energy e and the expected reward r from system interactions. This determines whether a system transition between ablative, absorptive, or ambivalent.

$$B_c(t) = \Sigma(e, r)$$

Utilizing the function above we can demonstrate transition cascades based on the relationship between e r

$$\Sigma(e, r) = \begin{cases} \text{Ablative}, & \text{if } e < \theta_1 \text{ and } r < \rho_1 \\ \text{Absorptive}, & \text{if } \theta_1 \leq e < \theta_2 \text{ and } r \geq \rho_1 \\ \text{Ambivalent}, & \text{if } e \geq \theta_2 \text{ and } r \geq \rho_2 \end{cases}$$

Therefore:

$$B_c(t) = \Sigma\left(\frac{E_{\text{stored}}(t)}{1 + \Phi_{ij}},\ \hat{R}_t\right)$$

Where:

- $e = \dfrac{E_{\text{stored}}(t)}{1 + \Phi_{ij}}$: Internal energy discounted by boundary interaction pressure.
- $r = \hat{R}_t$: Predicted reward from boundary interactions.
- θ_1, θ_2: Energy thresholds for strategic transitions.
- ρ_1, ρ_2: Reward thresholds for absorptive or neutral engagement.

This function governs how systems adjust their posture in response to internal resilience and external opportunity. It determines whether the system allocates more energy to boundary defense, exploration, or integration with other systems.

4 Energy Allocation and Boundary Dynamics

In this framework, a system dynamically allocates internal energy to either maintain action vector alignment among its components, thus influence boundary or to perform boundary functions such as filtering or state transition. This alignment determines the internal pressure applied to the system boundary, which, in turn, interacts with external pressures from other systems to determine the boundary's behavior.

The viability of the system is governed by how this internal alignment pressure supports or fails to support a stable boundary given the interaction constraints imposed by the environment.

4.1 Internal Alignment Determines Boundary Pressure

The system allocates energy to reduce divergence between its components' action vectors. This process distributes the internal cumulative component vector field as a pressure gradient along the interior of the boundary. The variability of component vector field pressure along boundary sections, will drive boundary state transitions for those boundary sections that cascade component vector interactions across the component adjacency field w_i.

Let:

$$C_{\text{align}}(t) = \sum_{i=1}^{n} w_i \left\| \vec{a}_i(t) - \hat{A}_S(t) \right\|$$

where:

- $\vec{a}_i(t)$ is the action vector of component i at time t
- $\hat{A}_S(t)$ is the consensus direction of the system
- w_i is the weighting (influence or contribution) of component i described previousl in section 3.2

This reflects how effectively internal energy contributes to outward pressure against the boundary. Alignment determines the efficiency energy is allocated to boundary interactions

$$E_{\text{available}}(t) = E_{\text{stored}}(t) - C_{\text{align}}(t)$$

This available energy forms the system's internal pressure gradient Π_{int}:

$$\Pi_{\text{int}} = f(E_{\text{available}}, \partial(S), |\mathcal{A}|)$$

4.2 Boundary State as a Function of Internal and External Pressure

The system boundary enters into a state transition based on the interaction between internal pressure and external constraints from surrounding systems. We model this using the boundary state transition function:

$$B_c(t) = \Sigma\left(\frac{\Pi_{\text{int}}(t)}{1+\Phi_{ij}},\ \hat{R}_t\right)$$

where:

- Φ_{ij} is the interaction pressure from adjacent system boundaries
- $\hat{R}_t$ is the predicted environmental reward from forward modeling
- $\Sigma(e, r)$ returns a boundary state: Ablative, Absorptive, or Ambivalent

This function determines whether the system boundary:

- Resists external systems (Ablative)
- Integrates with external systems (Absorptive)
- Ignores external systems (Ambivalent)

The pressure differential defines the boundary's permeability in an absorptive state, extractive costs to other systems in the ablation state, or passivity in the ambivalent state.

4.3 Boundary Energy Cost Based on State and Pressure Field

Once the boundary enters a particular state $B_c(t)$, its maintenance cost is computed based on the current configuration, external interaction pressure, and reward density:

$$B_t = \frac{f(\partial(S_t), R_t, \Phi_{ij}, B_c(t))}{\kappa_t}$$

where:

- $\partial(S_t)$: measurable boundary structure at time t
- R_t: environmental resource density
- Φ_{ij}: sum of constraint pressure from interacting system boundaries
- $B_c(t)$: active boundary state
- κ_t: stability margin (see below)

This cost reflects the difficulty of maintaining the current state given both internal and external constraints.

4.4 Stored and Available Energy

The system's usable energy at time t is:

$$E_{\text{stored}}(t) = \int_{t-\Delta t}^{t} [E_{\text{gain}}(t') - B_t(t')]\, dt'$$

and the energy available for boundary pressure is:

$$E_{\text{available}}(t) = E_{\text{stored}}(t) - C_{\text{align}}(t)$$

4.5 Stability Margin κ_t

The boundary's resistance to collapse is governed by the stability margin:

$$\kappa_t = \frac{E_{\text{available}}(t)}{\alpha \cdot |\partial(S_t)| + \beta \cdot E_{\text{motion}}(t)}$$

where:

- $|\partial(S_t)|$ is the size/complexity of the boundary
- $E_{\text{motion}}(t)$ is energy allocated to movement or growth
- α, β are domain-dependent weights

4.6 Environmental Reward Prediction and Extraction

The system predicts environmental affordances:

$$E_{\text{gain}}(t) = \eta \cdot U(\hat{R}_t)$$

where:

- η is the external system exploitability coefficient
- $\hat{R}_t = \Pi(S_t, S_{t-1}, ..., S_{t-\mu})$ is the predicted environmental reward based on memory μ
- $U(\cdot)$ is the domain defined, learned or inherited utility function, mapping predictions to usable energy

This value increases stored energy, and in turn, increases the amount of energy that may reach the boundary if alignment is high.

4.7 Summary

This model replaces the traditional exploration vs. exploitation tradeoff with a unified alignment-pressure paradigm. The system does not explicitly choose between goals. It aligns internal components; this alignment becomes pressure; that pressure determines boundary state; and boundary state determines whether cohesion can be sustained.

In this framework, exploration and maintenance are not opposing strategies they are both emergent consequences of boundary dynamics under energy constrained component alignment.

5 Inter-System Interaction Function $\Psi(B_i, B_j)$

System - System interactions are mediated exclusively through their boundaries. Every inter-system relationship, whether cooperative, competitive, or neutral, manifests as a change in the cost of maintaining and exploiting each system's own boundary.

We define the interaction function $\Psi(B(S_i), B(S_j))$ as the sum of constraint-induced cost differentials each system imposes on the other's boundary dynamics.

$$\Psi(B(S_i), B(S_j)) = \Delta C_i + \Delta C_j$$

Where:

$$\Delta C_i = C_{S_i|S_j}^{\text{explore/exploit}} - C_{S_i}^{\text{explore/exploit}}$$
$$\Delta C_j = C_{S_j|S_i}^{\text{explore/exploit}} - C_{S_j}^{\text{explore/exploit}}$$

and:

- $C_{S_i}^{\text{explore/exploit}}$: The baseline cost for S_i to explore or exploit the environment in the absence of S_j.
- $C_{S_i|S_j}^{\text{explore/exploit}}$: The new cost for S_i to perform the same actions in the presence of S_j, including any constraints or interference resulting from $B(S_j)$.

5.1 Interpretation of Ψ

The sign and magnitude of $\Psi(B(S_i), B(S_j))$ provide a scalar interpretation of relational alignment or conflict between two systems:

- $\Psi > 0$: The presence of each system increases cost for the other. This reflects competitive, ablative, or parasitic interaction.

- $\Psi < 0$: Each system lowers cost for the other. This reflects symbiotic or absorptive interaction.
- $\Psi \approx 0$: The systems have negligible impact on one another's boundary dynamics. This reflects ambivalence or passive coexistence.

5.2 Local Interaction Gradient $\nabla\Psi$

We define the directional constraint gradient between two systems as:

$$\nabla\Psi_{i\to j} = \frac{\Delta C_j}{\Delta C_i + \epsilon}$$

where ϵ is a known, biasing, positive constant to prevent division by zero. This gradient expresses:

- How strongly S_i is constraining S_j relative to how constrained it is in return.
- The asymmetry of influence or suppression between boundary configurations.

A large positive $\nabla\Psi_{i\to j}$ implies that S_i is exerting dominance or drag over S_j. A large negative value implies S_j is leveraging or overwhelming S_i.

5.3 Environment is the Sum of System Interactions

I define the local environmental field $\mathcal{E}_t$ experienced by any given system S_i as the sum of all pairwise interaction functions with other present systems:

$$\mathcal{E}_t(S_i) := \sum_{j\neq i} \Psi(B(S_i), B(S_j))$$

This emergent field replaces the need for a metaphysical or pre-defined global "environment." The environment, in this theory, is constructed from the total cost interactions that a system's boundary must negotiate over time.

5.4 Interaction Pressure in the Cohesion Function

The total pressure from the environment enters into the cohesion calculation for S_i via the boundary maintenance term:

$$B_t^*(B(S_i)) = B_t + C_{\text{align}}(t) + \sum_{j\neq i} \Psi(B(S_i), B(S_j))$$

This allows the cohesion function $\gamma(B(S_i))$ to reflect both internal misalignment and external relational drag without the need for higher-level aggregation functions. Boundary integrity is thus always evaluated in context.

6 Toy Example: Grass Asphalt System interaction

I consider the interaction between two systems:

- S_g: a viable seed system (grass) with exploratory capacity.
- S_a: a rigid boundary system (asphalt) with low adaptivity and high structural integrity.

Each system is defined entirely by its boundary:

$$S_g := B(S_g)[\mathcal{A}_g] \qquad S_a := B(S_a)[\mathcal{A}_a]$$

where:

- $B(S_g)$: a semi-permeable, environmentally sensitive boundary (seed coat, membrane).
- $B(S_a)$: a non-permeable, high-friction artificial surface (compacted hydrocarbon lattice).
- $\mathcal{A}_g$: internal energy storage, temperature and light sensors, growth pressure.
- $\mathcal{A}_a$: inert structural coherence; minimal active internal dynamics.

At time $t = 0$, the system S_g exists under S_a, in an environment with minimal sunlight, low temperature, and little moisture. The boundary state of S_g is therefore inert (ambivalent), while S_a exerts passive structural constraint.

6.1 Boundary States and Energy Conditions

$$B_c^{(g)}(t) = \Sigma\left(\frac{E_{\text{stored}}^{(g)}(t)}{1+\Phi_{g,a}},\ \hat{R}_t^{(g)}\right)$$

Where:

- $E_{\text{stored}}^{(g)}(t)$: energy stored in seed tissue and mitochondria.
- $\Phi_{g,a} = f(\partial(S_g), \partial(S_a), R_t)$: boundary interaction pressure based on thermal constriction, water impermeability, and surface composition.
- $\hat{R}_t^{(g)} = \Pi(R_t)$: grass prediction of environmental resources, especially temperature and photonic energy.

In cold months, $B_c^{(g)}(t) =$ Ambivalent due to low $E_{\text{stored}}^{(g)}$ and suppressed $\hat{R}_t^{(g)}$.

As ambient temperature increases and light begins to reach cracks in the asphalt, the expected environmental reward $\hat{R}_t^{(g)}$ increases. This leads to a boundary state shift:

$$B_c^{(g)}(t + \Delta t) \to \text{Absorptive}$$

as roots initiate penetration into soil beneath asphalt. Simultaneously, the asphalt system S_a experiences micro-fracture and dilation due to thermal expansion and biological pressure.

6.2 Interaction Function $\Psi(B(S_g), B(S_a))$

I define the directional constraint function between S_g and S_a:

$$\Psi(B(S_g), B(S_a)) = \Delta C_g + \Delta C_a$$

Where:

$$\Delta C_g = C_{S_g|S_a}^{\text{explore}} - C_{S_g}^{\text{explore}}$$
$$\Delta C_a = C_{S_a|S_g}^{\text{integrity}} - C_{S_a}^{\text{integrity}}$$

with:

- $C_{S_g}^{\text{explore}}$: cost for grass to explore in open soil.
- $C_{S_g|S_a}^{\text{explore}}$: increased cost under the constraint of asphalt.
- $C_{S_a}^{\text{integrity}}$: baseline cost of maintaining asphalt structure in absence of biological intrusion.
- $C_{S_a|S_g}^{\text{integrity}}$: new cost due to root expansion, water ingress, and heat cycling.

6.3 Cohesion Dynamics

The scalar cohesion of the grass system is computed as:

$$\gamma(B(S_g)) = \left[\frac{B_t^{(g)} + C_{\text{align}}^{(g)}(t) + \Psi(B(S_g), B(S_a))}{\kappa_t^{(g)}}\right] + \eta_g \cdot U(\hat{R}_t^{(g)}) + \frac{H(S_{t+1}^{(g)}) - H(S_{t+1}^{(g)} \mid \hat{S}_{t+1}^{(g)})}{g(\mu, \lambda_t, \tilde{M}_t)} + \tau$$

The cohesion of the asphalt system is:

$$\gamma(B(S_a)) = \left[\frac{B_t^{(a)} + \Psi(B(S_a), B(S_g))}{\kappa_t^{(a)}}\right] + \eta_a \cdot U(\hat{R}_t^{(a)}) + \tau$$

Since S_a lacks active prediction, exploration, or feedback capacity, its prediction efficiency and alignment terms vanish. The system is inertial, and its viability depends only on stored structural energy and interaction pressure.

6.4 Outcome

Over time, the cohesion $\gamma(B(S_g))$ rises due to improved predictions and environmental adaptation. The cohesion $\gamma(B(S_a))$ declines due to increased cost of boundary preservation and lack of internal responsiveness.

Eventually:

$$\gamma(B(S_a)) < \gamma_{\min} \quad \Rightarrow \quad \text{Boundary failure}$$

resulting in cracking, fragmentation, and ecological succession. The grass system absorbs the local niche, and the asphalt dissolves as a coherent boundary system.

6.5 System-Theoretic Insight

This interaction demonstrates the key principle of boundary-centric modeling: Systems do not persist due to interior mass or intent, but due to energy-efficient maintenance of selective interfaces in relation to their environment and other systems.

Even a high-inertia structure like asphalt, when unable to predict, adapt, or reallocate energy in the face of $\Psi > 0$, will collapse against a biologically minimal system capable of adaptive modeling and absorptive growth.

7 Intuition for Derivation

Humans are medium sized objects and as a result have a sensor range and tool building capacity that can scale to observation for the smallest things (fermions and beyond) as well as the largest things (Cosmic Background Microwave)

Cohesion begins with the simplest possible systems: bound fermion pairs, whose stability depends solely on internal binding energy relative to external environmental stress. These systems have no capacity to model or respond to their environment; their cohesion is passive and dissolves if the external energy exceeds their bond strength.

As complexity increases through cooperative or consumptive bonding systems begin to alter or stabilize their local environments. Feedback mechanisms emerge, allowing systems to maintain cohesion through basic forms of environmental interaction. At this level, boundaries become semi-permeable and regulated by internal dynamics.

Eventually, some systems evolve internal representations of their environment. In intelligent organisms, this takes the form of symbolic modeling, memory, and simulation. Cohesion is no longer reactive it becomes strategic. Such systems predict future states, differentiate self from world, and actively shape interactions to preserve or increase their stability.

8 Proposed Lemma: Life as Substructure with Prediction

Lemma.
Let $\mathcal{S}$ be a bounded system of fermion-level components. Then $\mathcal{S}$ can only exhibit prediction, adaptive search, or sustained internal cohesion if:

1. It contains at least two interacting components with cumulative action vectors;
2. It maintains a boundary through stored energy or adaptive maintenance;
3. It differentiates internal from external state with a predictive model I_t.
4. living systems emerge as constrained solutions to the problem of maintaining complex system cohesion in dynamic environments