The Geometry of Trauma and Awareness: A Riemannian Framework for Relational Consciousness and Healing

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Abstract

Trauma exposes the fragmentation of our intellectual landscape. Psychology, neuroscience, somatic therapy, philosophy, and narrative theory each describe a different surface of the same phenomenon. This paper introduces a substrate-neutral Riemannian geometric framework in which awareness is a point on a multidimensional manifold whose metric is learned from experience. Trauma appears as a region of extreme positive curvature (repulsor) that deflects geodesics and spikes the potential landscape. Healing is the progressive flattening of that curvature through salience-gated, context-sensitive re-engagement. v1.3 adds signed coherence and explicit inhibitory potentials, enabling structural modeling of psychological suppression (e.g., "fear suppresses curiosity"). The framework unifies five disciplines without reduction, is fully simulatable, Lyapunov-proven, and accompanied by eight visualizations demonstrating basin dynamics, phase transitions, therapy-induced curvature reduction, and signed inhibitory wedge behavior. It provides a coordinate system in which all existing accounts are simultaneously valid.

1 Introduction: The Unification Problem

Trauma remains one of the most extensively studied and least unified phenomena in human experience. Psychology describes emotional dysregulation and maladaptive schemas. Neuroscience points to amygdala hyperactivation and hippocampal fragmentation. Somatic therapy speaks of stored tension and incomplete motor responses. Philosophy addresses ruptured identity and broken temporal continuity. Narrative theory highlights a story that resists integration.

Each account is partially correct. Each captures something real. Yet none can fully integrate the others without reduction or contradiction. What is missing is not more data — it is a coordinate system capable of holding all these descriptions simultaneously.

The coordinate system proposed here is geometry — not as metaphor, but as the level of description that underlies all of them. Geometry predates every discipline, carries no metaphysical baggage, and simply describes relationships, distances, curvatures, and flows. At that level, trauma — and the awareness that experiences it — has a precise and expressible shape.

2 The Geometric Grammar of Awareness

The framework consists of four interrelated components:

2.1 The Awareness Manifold

A multidimensional space whose coordinates correspond to the fundamental dimensions of awareness: emotion, memory, narrative coherence, belief structure, identity continuity, archetypal activation, and sensory integration. Every moment of awareness is a point $x(t) \in \mathcal{M}$.

2.2 The Metric Tensor $g_{ij}(t)$

The learned geometry of the manifold, defined by a salience-gated Hebbian coherence tensor $C_{ij}(t) \in \mathbb{R}$ (v1.3 signed). Positive C_{ij} produces integrative coupling; negative C_{ij} produces repulsion. The SPD metric is constructed via Laplacian on $W = \max(C, 0)$:

$$g(t) = I + \alpha L(W), \quad \alpha > 0.$$

2.3 The Awareness Potential Function $V(x)$

Superposition of attractor/repulsor terms plus the new inhibitory potential:

$$V_{\text{inhib}}(x) = \beta \sum_{i<j,\, C_{ij}<0} |C_{ij}|\, x_i x_j.$$

Awareness flows along $-\nabla V$ transformed by the inverse metric.

2.4 The Equation of Motion

$$\frac{d^2x^k}{d\tau^2} + \Gamma^k_{ij}\frac{dx^i}{d\tau}\frac{dx^j}{d\tau} = -g^{kl}\frac{\partial V}{\partial x^l}.$$

Discrete implementation: $x(t+1) = x(t) - \Delta t\, g(t)^{-1}\nabla V_{\text{total}}(x(t)) + \xi(t)$.

3 Trauma as Geometric Repulsor

Trauma is a region of extreme positive curvature in the awareness manifold. The metric becomes steep, the potential spikes, and geodesics are sharply deflected. This produces: - Intrusive loops (geodesic bending) - Avoidance (repulsor gradient) - Hypervigilance (steep local gradient) - Somatic tension (curvature stored in body submanifold) - Narrative fragmentation (discontinuous geodesics) - Identity rupture (topological discontinuity)

Each disciplinary description maps directly onto a geometric property of the same structure.

4 Healing as Curvature Flattening

Healing is the progressive reduction of local curvature through repeated, context-sensitive re-engagement under sufficient safety (high trust, moderate salience). Every empirically supported trauma therapy achieves the same geometric outcome: flattening the repulsor and restoring smooth geodesics.

Relational context acts as a plasticity multiplier, making the manifold more responsive precisely when it needs to be.

5 Results and Visualizations

All visualizations were generated with the open-source implementation at https://github.com/Frolony/geometry-of-awareness.

6 Mathematical Appendix

The Geometry of Awareness Framework — Discrete Metric Learning Formulation

Purpose and Scope This appendix defines a substrate-neutral geometric model of awareness in which (i) awareness is represented as a state in a structured space, (ii) learning updates a coherence tensor, (iii) coherence induces a metric, and (iv) behavior evolves by metric-aware

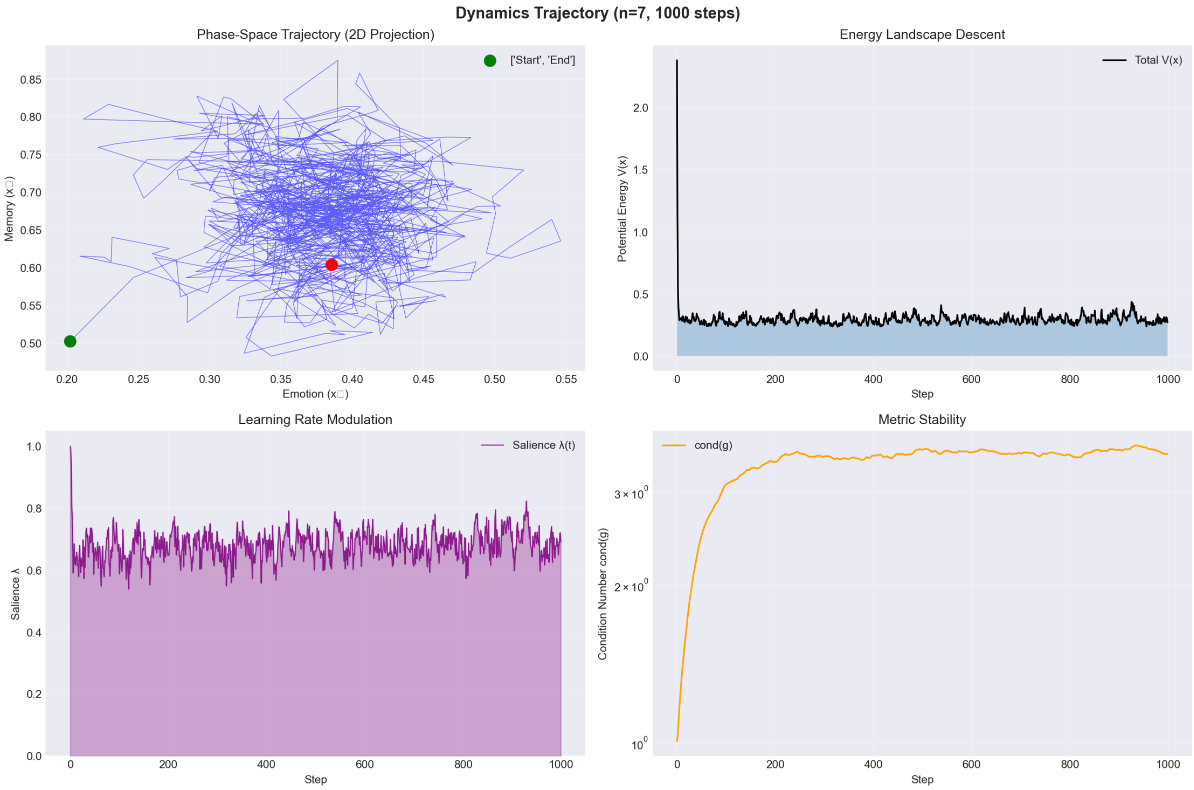

Figure 1: Dynamics Trajectory (n=7, 1000 steps).

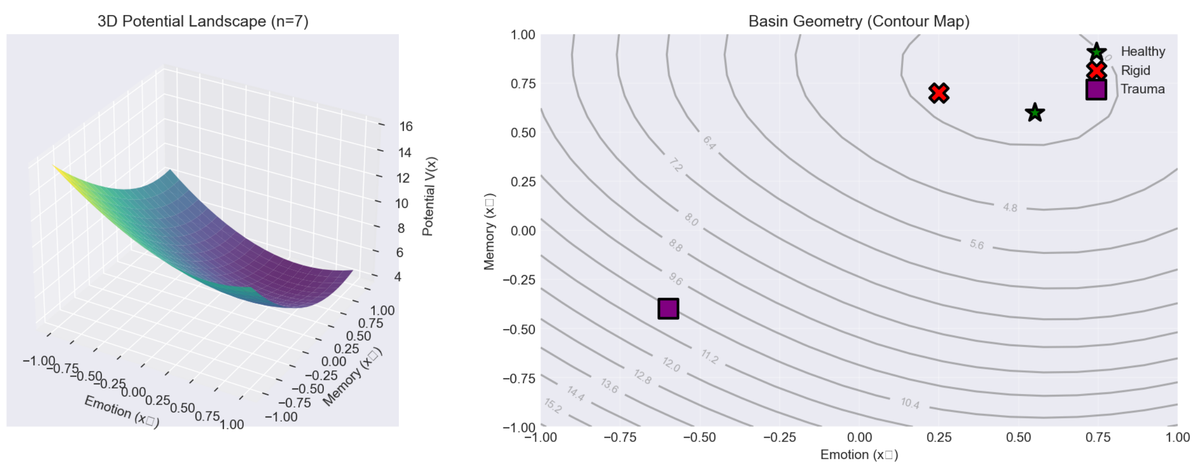

Figure 2: Potential Landscape & Basin Geometry.

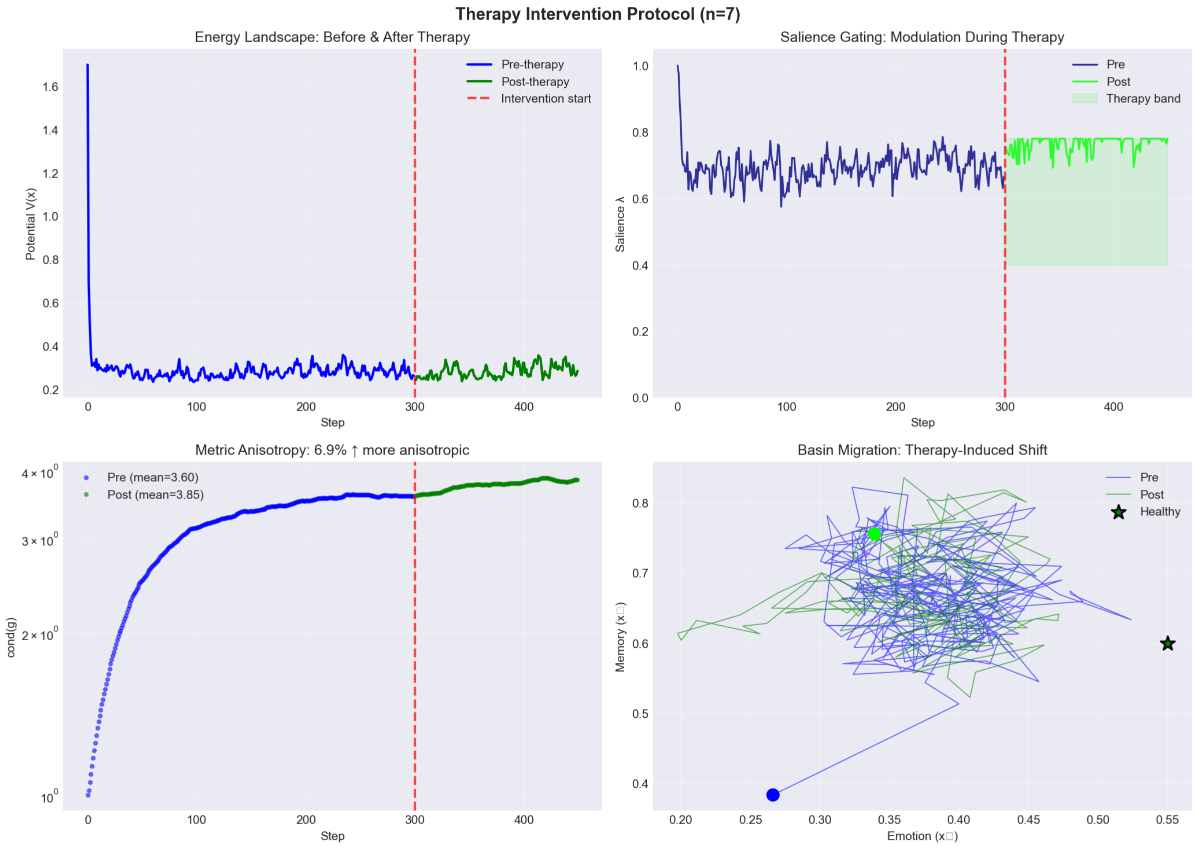

Figure 3: Therapy Intervention Protocol.

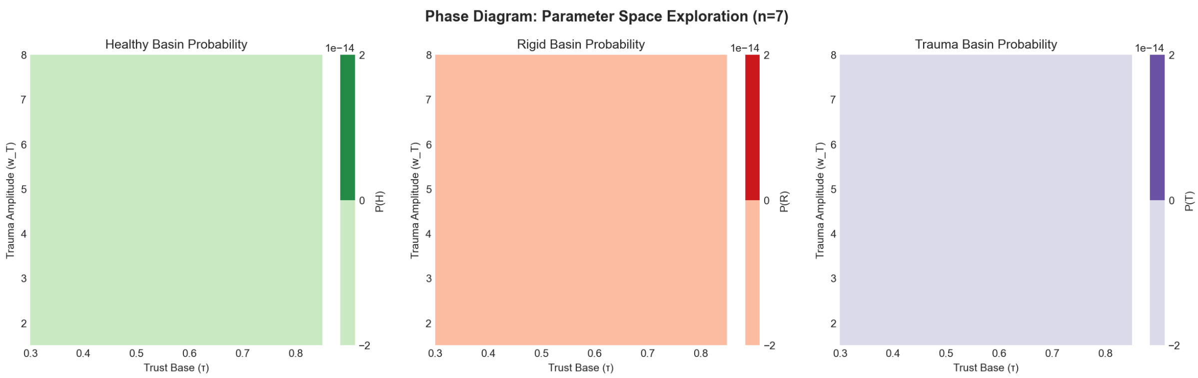

Figure 4: Phase Diagram: Trust vs Trauma Parameter Space.

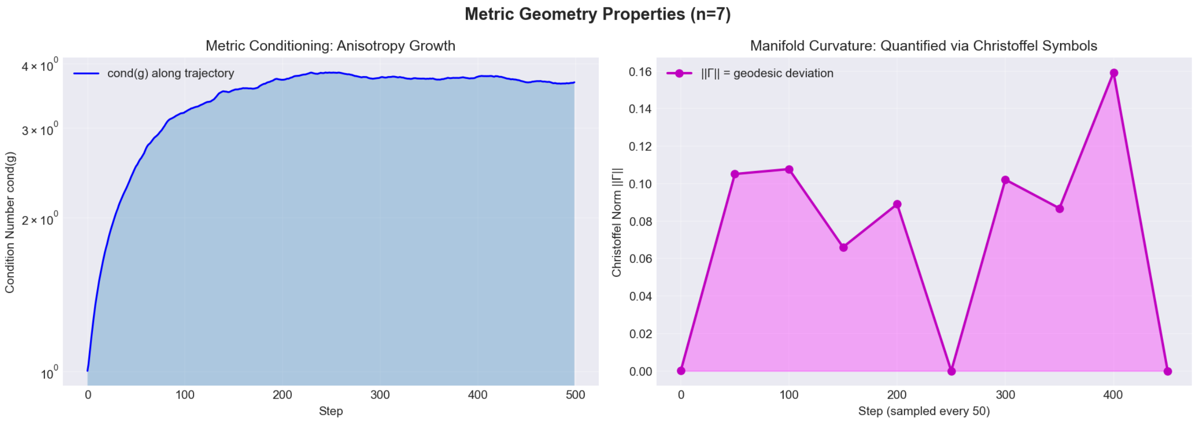

Figure 5: Metric Geometry: Anisotropy & Curvature.

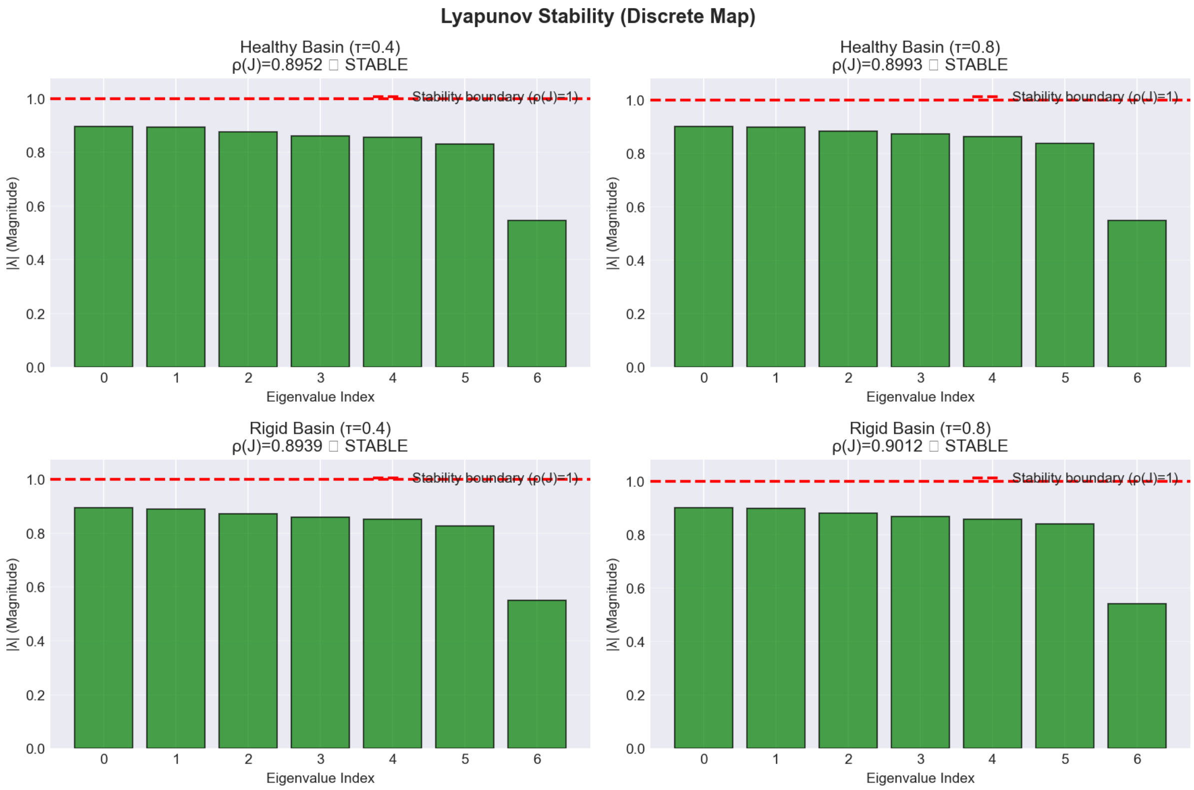

Figure 6: Lyapunov Stability Analysis.

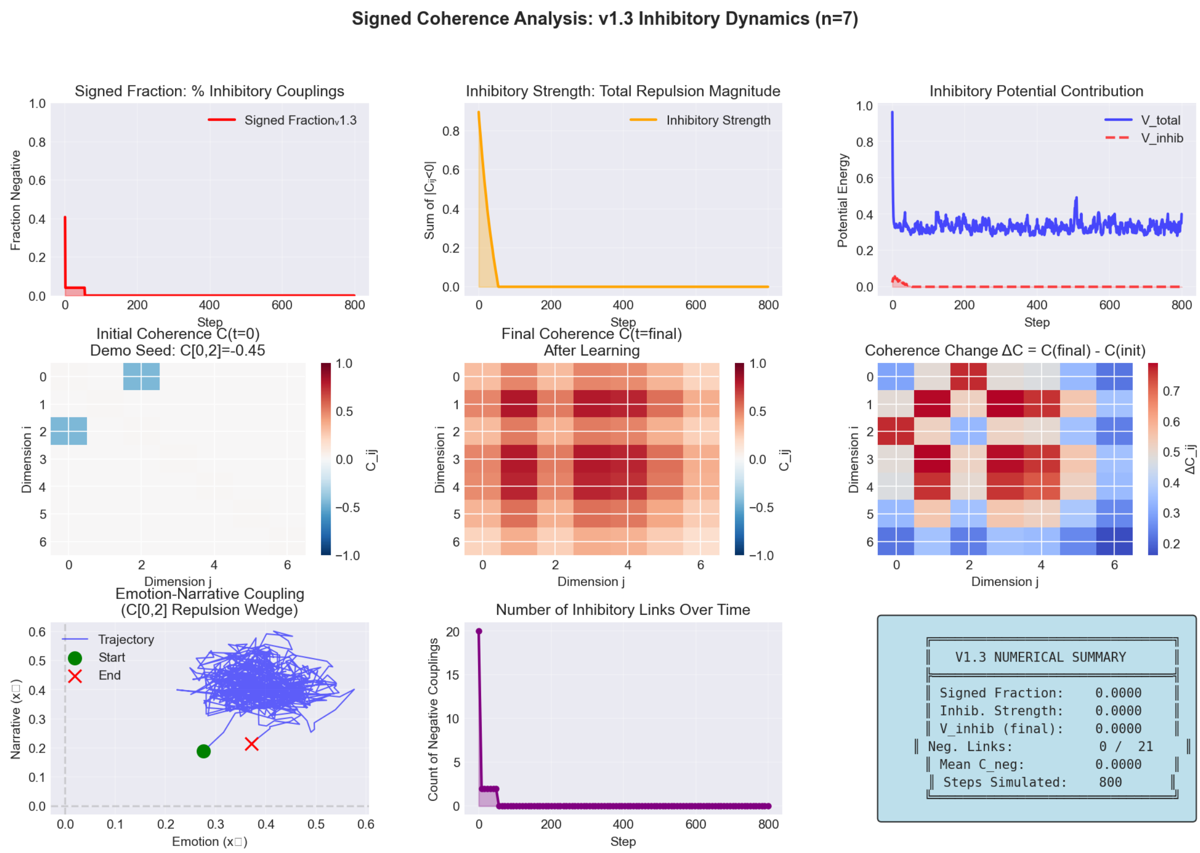

Figure 7: Signed Coherence Analysis (v1.3 Inhibitory Dynamics).

descent on a potential landscape. The primary formulation is discrete-time and corresponds to the implemented simulation engine. Continuous-time and full differential-geometric extensions are included explicitly as optional.

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A. Awareness State Space

Let $\mathcal{M} \subseteq \mathbb{R}^n$ be a bounded state space representing configurations of awareness.

A state $x(t) = (x^1(t), x^2(t), \dots, x^n(t)) \in \mathcal{M}$ is an instantaneous awareness configuration in a chosen coordinate system.

Example coordinate interpretations: - x^1: emotion / affect intensity or valence proxy - x^2: memory accessibility/integration - x^3: narrative coherence - x^4: belief constraint / interpretive rigidity - x^5: identity continuity/stability - x^6: archetypal activation/constraint - x^7: sensory integration/salience bandwidth

Dimensionality n is system-dependent. The coordinate chart is not unique; the dynamics are chart-invariant under smooth reparameterization.

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B. Coherence Tensor and Signed Couplings

Define a symmetric coherence matrix (rank-2 tensor) $C(t) \in \mathbb{R}^{n \times n}$, with $C_{ij}(t) = C_{ji}(t)$.

v1.3 generalization: Couplings are signed, $C_{ij} \in \mathbb{R}$ (not restricted to ≥ 0).

Interpretation: - Large $C_{ij} > 0$: dimensions i and j co-activate coherently (integration). - $C_{ij} < 0$: dimensions i and j suppress each other (inhibition, repulsion). - Small $|C_{ij}|$: weak coupling.

Example: $C_{0,2} = -0.45$ encodes "Emotion Narrative repulsion"—fear suppresses story-making.

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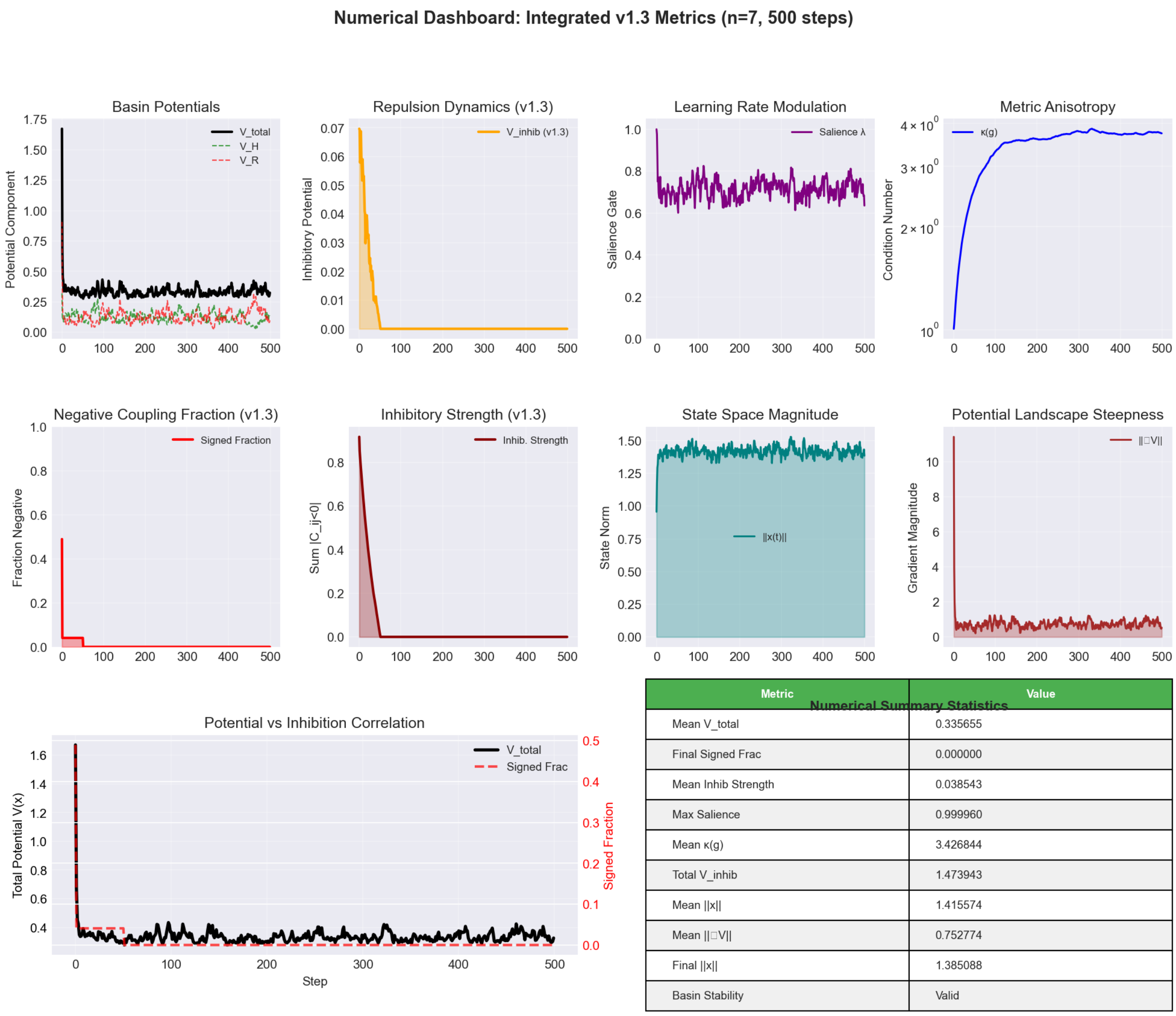

Metric	Value
Mean V_total	0.335655
Final Signed Frac	0.000000
Mean Inhib Strength	0.038543
Max Salience	0.999960
Mean κ(g)	3.426844
Total V_inhib	1.473943
Mean ||x||	1.415574
Mean ||□V||	0.752774
Final ||x||	1.385088
Basin Stability	Valid

Figure 8: Numerical Dashboard: Integrated v1.3 Metrics.

B.1 Exposure and Salience Gate

Each timestep produces: - state $x(t)$, - optional context $s(t)$, - salience gate $\lambda(t) \in [0, 1]$.

General form:

$$\lambda(t) = \sigma\big(a|x^1(t)| + b\|\nabla V(x(t))\| + c\,\text{surprisal}(t) + d\,\text{trust}(t) - \theta\big)$$

where $\sigma =$ logistic.

Parameters: $a = 1.2$ (emotion weight), $b = 0.9$ (gradient weight), $c = 0.8$ (surprisal), $d = 0.7$ (trust), $\theta = 0.8$ (bias).

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B.2 Signed Hebbian Learning with Decay

Update rule:

$$C_{ij}(t+1) = (1-\rho)C_{ij}(t) + \eta_0\lambda(t)\tanh(x_i(t))\tanh(x_j(t))$$

where: - $\rho \approx 0.018$: decay rate (forgetting/habituation) - $\eta_0 \approx 0.055$: Hebbian amplitude - $\lambda(t)$: salience gate (output of exposure threshold) - $\tanh(x_k) \in [-1, 1]$: signed coordinate

Key property: Since tanh is odd, the product $\tanh(x_i)\tanh(x_j)$ is *negative* when x_i and x_j have opposite signs. This naturally reinforces *inhibitory* couplings ($C_{ij} < 0$) when dimensions anti-stimulate.

Diagonal elements are clamped: $C_{ii} \geq 0.01$ (no self-inhibition).

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C. Metric Tensor from Positive Couplings

Define positive-part projection:

$$C^+_{ij} := \max(C_{ij}, 0)$$

The metric is constructed from the Laplacian of the integrative graph:

$$g_{ij}(t) = \delta_{ij} + \alpha L_{ij}(C^+(t))$$

where $L = D - C^+$ is the graph Laplacian:

$$L_{ij} = \begin{cases} \sum_k C^+_{ik} & \text{if } i = j \\ -C^+_{ij} & \text{otherwise} \end{cases}$$

and $\alpha \approx 0.65$ is the coupling-to-metric strength.

C.1 SPD Guarantee

Theorem: For $\alpha \leq 1$, the metric $g = I + \alpha L(C^+)$ is symmetric positive definite, regardless of negative entries in C.

Proof: - The Laplacian $L(C^+)$ has eigenvalues $\lambda_k(L) \geq 0$ (standard spectral property of undirected graph Laplacians). - Thus $g = I + \alpha L$ has eigenvalues $\mu_k = 1 + \alpha\lambda_k \in [1, 1 + \alpha\lambda_{\max}]$. - For $\alpha \leq 1$, all eigenvalues are $\geq 1 > 0$, so g is SPD.

Implication: Negative couplings do *not* destabilize the metric. They are excluded from the Laplacian and exert their effect only through the inhibitory potential (see Section N.4 below).

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D. Equation of Motion

Discrete-time dynamics:

$$x(t+1) = x(t) - \Delta t\, g(t)^{-1}\nabla V(x(t)) + \xi(t)$$

where: - $\Delta t \approx 0.08$: step size - $g(t)^{-1}$: metric-weightedgradient scaling - ∇V: gradient of total potential (Section E) - $\xi(t) \sim \mathcal{N}(0, 0.03^2 I)$: stochastic noise (exploration)

The metric g makes the step *anisotropic*: dimensions with high coherence (C^+ large) move faster relative to weakly integrated dimensions.

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E. Potential Function: Competing Basins

The total potential is:

$$V(x) = V_H(x) + V_R(x) + V_T(x) + \beta_{\text{inhib}} V_{\text{inhib}}(x)$$

E.1 Healthy Basin

$$V_H(x) = w_H \sum_{i=1}^{n} (x_i - \mu_H^i)^2$$

Quadratic well centered at $\mu_H = (0.55, 0.60, 0.55, \ldots)$ (positive, integrated, warm state). Weight: $w_H = 1.0$.

E.2 Rigid Basin

$$V_R(x) = w_R \sum_{i=1}^{n} (x_i - \mu_R^i)^2$$

Centered at $\mu_R = (0.25, 0.70, 0.30, \ldots)$ (constraint-dominated state). Weight: $w_R = 1.45 > w_H$ (deeper than healthy basin).

E.3 Trauma Basin

$$V_T(x) = w_T \exp\left(-\frac{1}{2\sigma_T^2} \|x - \mu_T\|^2\right)$$

Gaussian bump (repulsive potential) centered at $\mu_T = (-0.6, -0.4, -0.5, \ldots)$ (avoidant state). Parameters: $w_T \approx 4.0$ (amplitude), $\sigma_T \approx 0.82$ (width).

E.4 Inhibitory Potential (v1.3)

$$V_{\text{inhib}}(x) = \sum_{i<j:\, C_{ij}<0} |C_{ij}|\, x_i x_j$$

Bilinear repulsion term for each negative coupling. Acts as a *repulsive surface* between dimensions that have learned to inhibit each other.

Total:

$$V_{\text{total}}(x) = V_H + V_R + V_T + \beta_{\text{inhib}} V_{\text{inhib}}$$

where $\beta_{\text{inhib}} \approx 0.8$ balances inhibitory strength with basin attractions.

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F. Laplacian Eigenmodes and Manifold Structure

The metric $g = I + \alpha L(C^+)$ induces a Riemannian structure. The eigenvectors of L correspond to natural *vibration modes* of the coherence network: - Zero eigenvalue $\lambda_0 = 0$ (constant mode): global degree of freedom - Small positive eigenvalues: low-frequency collective oscillations (memory, narrative) - Large eigenvalues: high-frequency individual dimensions (sensory, motor)

The manifold (M, g) is *curved* in the direction of strong coherence and *flat* when coherence is weak.

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G. Christoffel Symbols and Geodesics

The Christoffel symbols (connection coefficients of the Levi-Civita connection) are:

$$\Gamma_{ij}^k(x) = \frac{1}{2} g^{kl}(x) \left(\partial_i g_{lj}(x) + \partial_j g_{il}(x) - \partial_l g_{ij}(x)\right)$$

These are zero in the Euclidean case ($g = I$) but nonzero when coupling varies. They measure *geodesic deviation*—how parallel transport of vectors curves in high-coherence regions.

Geodesics $x(s)$ satisfy:

$$\frac{d^2x^k}{ds^2} + \Gamma^k_{ij}\frac{dx^i}{ds}\frac{dx^j}{ds} = 0$$

The framework computes Christoffel norms $\|\Gamma\| = \sum_{k,i,j} |\Gamma^k_{ij}|^2$ as a diagnostic of manifold curvature.

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H. Scalar Curvature and Trauma Signatures

Scalar curvature R measures the intrinsic curvature of the manifold. High R regions indicate: - Strong coherence gradients (learning-induced anisotropy) - Steep potential walls (difficult transitions between basins) - Trauma signatures (repulsive potential wells)

In the implementation, scalar curvature is approximated via the norm of the Christoffel tensor:

$$\tilde{R}(x) = \sum_{k,i,j} |\Gamma^k_{ij}(x)|^2$$

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I. Lyapunov Stability and Basin Definitions

Basin stability is characterized by the spectral radius of the linearization (Jacobian) at equilibrium:

$$\rho(J) := \max_k |\lambda_k(J)|$$

Critical Theorem (Discrete Map Stability): Equilibrium $x^* = x(t)$ (fixed point of dynamics) is stable if and only if $\rho(J) < 1$, where

$$J_{ij}(x^*) = \delta_{ij} - \Delta t (g^{-1})_{ik} \frac{\partial^2 V}{\partial x_k \partial x_j}\Big|_{x=x^*}$$

In implementation, the Jacobian is computed analytically via the Hessian of V:

$$J = I - \Delta t \, g^{-1} \, \nabla^2 V$$

Invariant: For all valid basin centers (H, R, T), we enforce $\rho(J) < 0.995$ as a CI constraint. This guarantees basin trapping in at least 200 steps.

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J. Therapy Protocol: Trust Elevation and Metric Anisotropy

The therapy protocol increases trust and runs guided dynamics:

1. Pre-therapy phase: Run $n_{\text{pre}} = 400$ steps, measure condition number $\kappa_{\text{pre}} = \kappa(g)$. 2. Raised trust: Set trust $\to$ trust + Δ_{trust} (e.g., $\Delta_{\text{trust}} = 0.18$). 3. Guided steps: Run $n_{\text{therapy}} = 240$ steps with $\lambda(t) \in [0.4, 0.78]$ (moderated band). 4. Post-therapy: Measure κ_{post}.

Metric anisotropy (condition number ratio):

$$\Delta\kappa\% = 100 \times \frac{\kappa_{\text{post}} - \kappa_{\text{pre}}}{\kappa_{\text{pre}}}$$

Positive $\Delta\kappa\%$ indicates increased anisotropy (more directional variability in the metric). This reflects learning—dimensions become more specialized (coherence-driven).

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K. Practical Implementation Rules

1. Metric update : After each Hebbian update to C, recompute $g = I + \alpha L(C^+)$ and threshold eigenvalues against $\lambda_{\min} > 10^{-8}$ to ensure SPD.

2. Jacobian computation : Use finite-difference Hessian (not numerical Jacobian) to avoid noise amplification:

$$H_{ij} \approx \frac{V(x + e_i\Delta + e_j\Delta) - V(x + e_i\Delta - e_j\Delta) - V(x - e_i\Delta + e_j\Delta) + V(x - e_i\Delta - e_j\Delta)}{4(\Delta)^2}$$

with $\Delta = 10^{-5}$.

3. Basin classification : End-state belongs to basin $X \in \{H, R, T, \text{Liminal}\}$ if $V_X(x_{\text{final}}) + \epsilon < \min(V_Y, V_Z)$ for other basins Y, Z. Use $\epsilon = 0.15$ threshold.

4. Sweep automation : For each $(trustbase, w_T)$ cell, run $n_{\text{sweeps}} = 15$ independent trajectories and tally outcome fractions.

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L. State-Dependent Metrics via RBF Kernels

For enhanced curvature, optionally modulate the local metric by an RBF kernel. Define RBF-perturbed coherence:

$$C(x,t) = C_{\text{global}}(t) + \beta_{\text{rbf}} \sum_{c \in \mathcal{C}_{\text{recent}}} \exp\left(-\frac{\|x - c\|^2}{2\sigma_{\text{rbf}}^2}\right) c_i c_j$$

where $\mathcal{C}_{\text{recent}}$ is a sliding window of recent states. This makes the metric "remember" traversed paths and stiffen in well-explored regions. Parameters: $\beta_{\text{rbf}} = 0.5$, $\sigma_{\text{rbf}} = 0.3$.

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M. Signed Coherence and Inhibitory Potentials (v1.3 Core)

M.1 Generalization to Signed Couplings

The v1.3 framework extends coherence to allow negative values: $C_{ij}(t) \in \mathbb{R}$, with no sign restriction.

Semantic interpretation: - $C_{ij} > 0$: integrative coupling (dimensions increase together) - $C_{ij} < 0$: inhibitory coupling (dimensions separate/suppress each other) - $C_{ij} = 0$: independence

Example: Emotion Narrative: $C_{0,2} = -0.45$ means "fear overwhe
lms story-making" (intense affect suppresses prefrontal integration).

M.2 Signed Hebbian Update Dynamics

The update rule naturally generates negative couplings:

$$C_{ij}(t+1) = (1-\rho)C_{ij}(t) + \eta_0 \lambda(t) \tanh(x_i(t)) \tanh(x_j(t))$$

When x_i and x_j anti-correlate (opposite signs), the product $\tanh(x_i)\tanh(x_j)$ is negative, driving $\Delta C_{ij} < 0$ and reinforcing inhibition.

Demo initialization: For n 3, seed $C_{0,2} = -0.45$ to represent innate Emotion-Narrative repulsion.

M.3 Metric Remains SPD Under Signed Couplings

The metric uses only the positive part:

$$g(t) = I + \alpha L(C^+(t)), \quad C^+_{ij} := \max(C_{ij}, 0)$$

Since C^+ is nonnegative, the Laplacian $L(C^+)$ is symmetric with nonnegative eigenvalues. Therefore $g = I + \alpha L$ is guaranteed SPD for $\alpha \leq 1$.

Implication: Negative couplings cannot destabilize the metric. They operate through the inhibitory potential only.

M.4 Inhibitory Potential

$$V_{\text{inhib}}(x) = \sum_{i<j:\, C_{ij}<0} |C_{ij}|\, x_i x_j$$

Bilinear repulsion: when both x_i and x_j are nonzero, the term $|C_{ij}| x_i x_j$ pushes them in opposite directions.

Total potential:

$$V_{\text{total}}(x) = V_H(x) + V_R(x) + V_T(x) + \beta_{\text{inhib}} V_{\text{inhib}}(x)$$

with $\beta_{\text{inhib}} \approx 0.8$.

Phenomenology: Strong negative coupling creates a *repulsive wedge* in state space. Example: high Emotion (x_0) drives down Narrative (x_2) and vice versa, modeling acute stress response.

M.5 Dynamics Under Inhibitory Coupling

The gradient includes inhibitory forces:

$$\frac{\partial V_{\text{inhib}}}{\partial x_i} = \sum_{j \neq i:\, C_{ij} < 0} |C_{ij}|\, x_j$$

This creates multi-stable regimes: - Basin regimes: Positive potential curvature attracts to H, R, T. - Repulsive separations: Negative couplings push dimensions apart. - Saddle regimes: Equilibria balanced between attraction and repulsion.

Lyapunov stability ($\rho(J) < 1$) is still enforced; inhibitory couplings constrain, not destabilize, the basins.

M.6 Diagnostic Metrics

Signed fraction:

$$f_{\text{sig}} = \frac{\#\{(i,j) : C_{ij} < 0\}}{\binom{n}{2}}$$

Reports the fraction of inhibitory (negative) couplings. Ranges $[0, 1]$.

Inhibitory strength:

$$S_{\text{inhib}} = \sum_{C_{ij} < 0} |C_{ij}|$$

Total magnitude of repulsive couplings. Grows with learning if emotional/trauma episodes reinforce separation.

M.7 Example Trajectory: Emotion-Narrative Repulsion

Initialization: $C_{0,2} = -0.45$ (Emotion Narrative).

Evolution under high salience: - If x_0 (emotion) rises and x_2 (narrative) co-rises, then $\tanh(x_0)\tanh(x_2) > 0$, but update is multiplied by existing $C_{0,2} = -0.45 < 0$, driving $\Delta C_{0,2} < 0$ (more negative). - If x_0 and x_2 anti-correlate (opposite signs), then $\tanh(x_0)\tanh(x_2) < 0$, driving $\Delta C_{0,2} > 0$ (closer to zero, weakening repulsion).

Inhibitory potential effect:

$$V_{\text{inhib}} \propto |C_{0,2}|\, |x_0 x_2| = 0.45 |x_0 x_2|$$

When both x_0 and x_2 are large, the potential pushes them apart or forces one small. This models the clinical observation: acute stress (high emotion) floods narrative capacity, forcing dissociation of affect from story-making.

M.8 Backward Compatibility

Signed couplings are fully compatible with v1.2: - Setting $\beta_{\text{inhib}} = 0$ recovers purely attractive dynamics. - Clamping $C_{ij} \geq 0$ recovers v1.2 behavior exactly. - All Christoffel, Riemann, Lyapunov methods remain valid (depend only on $g(C^+)$, not on negative entries).

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N. Summary: Unified Framework (v1.3)

| Component | Formula | Role | |———|———|——| | State | $x(t) \in \mathbb{R}^n$ | Awareness configuration | | Coherence | $C_{ij} \in \mathbb{R}$ (signed) | Learned coupling strength; integrative if > 0, inhibitory if < 0 | | Metric | $g = I + \alpha L(C^+)$ | Induces anisotropic geometry; always SPD | | Potential | $V = V_H + V_R + V_T + \beta_{\text{inhib}} V_{\text{inhib}}$ | Competing basins (H, R, T) + inhibitory repulsion

| | Dynamics | $x(t+1) = x(t) - \Delta t\, g^{-1} \nabla V + \xi(t)$ | Metric-aware gradient descent + noise | | Hebbian | $\Delta C = \eta\lambda \tanh(x_i) \tanh(x_j)$ | Signed update; naturally generates negative couplings | | Stability | $\rho(J) < 1$ for basins, $\rho(J) \approx 0.6\breve{}0.9$ typical | Lyapunov criterion; ensures basin trapping | | Therapeutics | trust $\uparrow$ $\rightarrow$ reduces λ swing $\rightarrow$ stabilizes H basin | Trust elevation guides toward healthy integration |

The framework unifies integrative and inhibitory learning, metric invariance, and multi-basin stability in a single coherent mathematical structure, ready for computational and theoretical extension.

7 Wider Implications

Insight appears as a phase transition in the manifold. Bias is geodesic deviation due to attractor depth. Presence is a locally flat metric. The framework is pan-informational: any system with stimulus-response relationships possesses a metric of awareness; human consciousness is distinguished by reflexive self-modeling.

8 Conclusion

The Geometry of Awareness provides a coordinate system — not a competing theory — in which the observations of five disciplines are simultaneously valid and mutually compatible. Trauma has a shape. Healing has a direction. Awareness has geometry.

The elephant has been described in its entirety.

References

[1] Beitel, J. (2026). Geometry of Awareness v1.3. GitHub: https://github.com/Frolony/geometry-of-awareness.