Field Theory of Semantic Dynamics: Empirical Validation Across Four Decades of Research

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ABSTRACT

We present a unified field theory of semantic dynamics in which cognitive states are represented as points in a pseudo-Euclidean space constructed from Galileo/Dort measurements. The space is characterized by a warp factor Ω, defined as the ratio of the algebraic sum of positive eigenvalues to the sum of absolute negative eigenvalues, which distinguishes qualitatively different types of pseudo-Riemannian geometry. A restart-diffusion field equation defines the equilibrium activation distribution, anchored by a collective source identified with Durkheim's *conscience collectif*. Individual systems are modeled as perturbations of the collective operator and anchor.

Communication events instantiate co-activation sets that generate forces as gradients of an explicit Hebbian potential, producing concept motion under a damped Newtonian equation with substrate-specific inertial mass (proportional to frequency of occurrence). The framework forms a closed seven-link chain — geometry to graph to field to weights to forces to motion to geometry — governed by a unified parameterization.

Empirical validation draws on four independent studies spanning 40 years: (1) Korean immigrant cultural convergence (1983), modeled as a damped dynamical system toward host-culture equilibrium; (2) Pigs in Space (2017), demonstrating that frequency predicts inertial mass with $r \approx .996$ and that a combined force–field model improves directional prediction from ≈.61 to ≈.83; (3) Nurses vs. Congress (2017), showing that source credibility affects motion direction rather than magnitude — credibility does not increase force magnitude; it changes force direction; and (4) Chevrolet–Volvo (2019), where the combined model achieves r ≈ .93–.96, resolving the previously puzzling perpendicular motion.

The unified model is:

$$\Delta \mathbf{x}_i = \frac{1}{m_i}\left(\mathbf{F}_{\mathrm{msg},i} + \beta \mathbf{B}\mathbf{x}_i\right)$$

where $\mathbf{F}_{\mathrm{msg}}$ is message-induced force, $\mathbf{B} = \mathbf{X}\mathbf{X}^T$ is the scalar product matrix defining the semantic field — the field operator — $m_i \propto f_i$ is inertial mass estimated from independent lexical frequencies, and $\beta = 1$ (no parameters estimated from outcome data). The theory specifies decision rules for replication across domains and substrates, including testable predictions about warp factor asymmetry under perturbation, spectral gap and cultural integration, and collective causal priority.

This framework integrates four decades of empirical research into a mathematically coherent, empirically validated field theory of semantic dynamics — applicable to humans, AI systems, and any intelligent system whose cognitive states can be represented as points in a measurable space.

Keywords: field theory, semantic dynamics, Galileo methodology, pseudo-Euclidean geometry, inertial mass, collective cognition, conscience collectif, Hebbian learning, Interactive Activation and Competition, cultural convergence, source credibility, persuasion

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1. INTRODUCTION

1.1 The Problem

For over a century, the measurement of meaning, attitude, and belief has relied on instruments — Likert scales, semantic differentials, rating scales — that project multidimensional semantic structures onto single axes. This approach rests on three assumptions that are empirically violated when full multidimensional measurement is applied:

1. Semantic change occurs along bipolar dimensions
2. All concepts can be meaningfully compared on these dimensions
3. The relevant geometry is implicitly assumed to be one-dimensional

As we demonstrate, cognitive processes operate in high-dimensional pseudo-Euclidean spaces where concepts exist as points with complex geometric relationships, where displacement follows Newton's second law with substrate-specific inertial mass, and where the forces governing change arise from the collective cognitive field rather than from individual psychological states. Traditional scales measure scalar projections of vector quantities, discarding the directional information that encodes the actual dynamics of meaning.

1.2 The Framework

This paper presents a mathematical framework adequate to the phenomenon. The framework has three components formally coupled into a single dynamical system:

The Geometric Component: Cognitive states are represented as points in a pseudo-Euclidean space $\mathbb{R}^{p,q}$, constructed from pairwise distance judgments via Torgerson's double-centering procedure. The space has both attractive (positive eigenvalue) and repulsive (negative eigenvalue) dimensions, whose relative proportion constitutes a measurable field invariant — the warp factor Ω. (In relativity theory, these are called spacelike and timelike, respectively, but we avoid that terminology here to prevent confusion with physics.)

The Dynamic Component: Cognitive change follows a damped Newtonian equation of motion with an explicit potential function, substrate-specific inertial mass governing resistance to displacement, Hebbian co-activation generating attractive forces derivable as energy gradients, and damping coefficients encoding the distinction between elastic (recoverable) and plastic (permanent) deformation.

The Sociological Component: The anchor distribution governing the field is not individual but collective — Durkheim's *conscience collectif* operationalized as a persistent distribution over the collective cognitive graph. Individual cognition is predicted from collective structure; the individual field is the collective field perturbed by individual history. The reason we stress the priority of the collective field is twofold: first, it is temporally prior to the existence of the individual instantiation — it already exists when individuals are born, and second, it persists beyond the lifetimes of the individual instantiations, continuing essentially unchanged even as the entire substrate is replaced.

1.3 Generality Across Intelligent Systems

The theory applies to any sufficiently complex intelligent system — not only humans, but artificial systems of any architecture, and non-human animals whose cognitive states can be represented as concepts with positions in a space. Whether any given system instantiates the field is an empirical question, not a definitional one. The same mathematics that describes attitude change in humans describes, in principle, the cognitive dynamics of crows solving novel problems, dogs responding to social primes, or language models processing conceptual perturbations. The substrate differs; the equations do not.

1.4 Overview of Empirical Validation

Supported by dozens of empirical studies, we have selected four independent studies spanning 40 years to provide converging evidence for the framework:

Study	Year	Domain	Key Finding
Korean Convergence	1983	Cultural assimilation	Damped dynamical system toward equilibrium
Pigs in Space	2017	Synonym inertia	Frequency predicts mass (r ≈ .996); combined model improves direction
Nurses vs. Congress	2017	Source credibility	Same magnitude, different direction — credibility changes direction, not force
Chevrolet–Volvo	2019	Brand persuasion	Combined model r ≈ .93–.96; perpendicular motion explained

Together, these studies demonstrate that semantic motion follows a unified Newtonian-like law: $\Delta\mathbf{x} = (\mathbf{F}_{\text{msg}} + \mathbf{Bx})/m$, with no parameters estimated from outcome data.

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2. THEORETICAL FRAMEWORK

2.1 Primitives and Type System

The theory distinguishes two kinds of cognitive objects: geometric states (where concepts live) and activation fields (how attention flows). In this paper, we represent cognitive states by the centroid of the activation field, which suffices for first-order dynamics. The full field — including its shape, gradient, and curvature — is in principle empirically determinable, even if precise measurement requires heroic effort.

Let $V = \{1, \dots, n\}$ index concepts (nodes).

Geometric State (Embedding): Each concept i has coordinates $\mathbf{y}_i(t)$ in pseudo-Riemannian space $\mathbb{R}^{p,q}$. The embedding at time t is $\mathbf{Y}(t) = (\mathbf{y}_1(t), \dots, \mathbf{y}_n(t))$. Let the metric tensor be $\eta = \mathrm{diag}(+1, \dots, +1, -1, \dots, -1)$.

For arbitrary $\mathbf{x}, \mathbf{y} \in \mathbb{R}^{p,q}$, the bilinear form is:

$$\langle \mathbf{x}, \mathbf{y} \rangle_{p,q} = \mathbf{x}^\top \eta \mathbf{y}$$

The squared interval between concepts i and j is:

$$s_{ij}^2(t) = \langle \mathbf{y}_i(t) - \mathbf{y}_j(t), \mathbf{y}_i(t) - \mathbf{y}_j(t) \rangle_{p,q}$$

Define the interval magnitude $d_{ij}(t)$ between concepts i and j:

$$d_{ij}(t) = \sqrt{|\, s_{ij}^2(t) \,|}$$

This preserves the full pseudo-Riemannian geometry implied by the measurements. No projection onto subspaces is performed and no eigenvalue directions are discarded. All dynamical quantities are defined in the metric determined by the eigenspectrum.

Activation Field (Graph State): At each moment in time, cognitive activation is distributed across the *n* concepts in V. This distribution is represented as a vector $\mathbf{a}(t)$ whose i-th entry gives the proportion of total activation assigned to concept i. Since activations are non-negative and must sum to 1, $\mathbf{a}(t)$ lives in the (*n*-1)-dimensional simplex Δ^{n-1}:

$$\mathbf{a}(t) \in \Delta^{n-1} = \{\mathbf{a} \in \mathbb{R}^n : \ a_i \geq 0, \sum a_i = 1\}$$

Coupling: geometry → graph operator → activation field → forces → geometry.

2.2 Measurement Map: Distances to Embedding

The theory requires that cognitive states be represented as points in a geometric space. Data are collected via the Galileo/Dort methodology, in which respondents make direct magnitude estimations of the dissimilarity between all pairs of concepts.

Let $\mathbf{D} = [D_{ij}]$ be the symmetric distance matrix from Galileo magnitude estimation. Torgerson double-centering yields a scalar product matrix $\mathbf{B} = [b_{ij}]$, where:

$$b_{ij} = -\frac{1}{2}(D_{ij}^2 - \bar{D}_{i\cdot}^2 - \bar{D}_{\cdot j}^2 + \bar{D}_{\cdot\cdot}^2)$$

The eigendecomposition of $\mathbf{B}$ is:

$$\mathbf{B} = \mathbf{Q}\mathbf{\Lambda}\mathbf{Q}^\top$$

where $\mathbf{Q} = [q_{ij}]$ is the matrix of (column) eigenvectors, and $\mathbf{\Lambda}$ is the diagonal matrix of eigenvalues.

Because $\mathbf{D}$ is constructed from empirical dissimilarity judgments, $\mathbf{\Lambda}$ may be indefinite — that is, it may contain both positive and negative eigenvalues. **This indefiniteness is not a defect to be corrected; it is an empirical finding about the structure of the cognitive space.**

The initial coordinates of concept i are:

$$\mathbf{y}_i(0) = (\sqrt{\lambda_1}q_{i1}, \dots, \sqrt{\lambda_p}q_{ip}, \sqrt{|\lambda_{p+1}|}\, q_{i,p+1}, \dots, \sqrt{|\lambda_{p+q}|}\, q_{i,p+q})$$

The absolute values in the second group ensure that the coordinates are real numbers; the fact that these dimensions arose from negative eigenvalues is carried instead by the metric tensor $\eta = \mathrm{diag}(+1, \dots, +1, -1, \dots, -1)$, which governs how distances are computed in the full pseudo-Euclidean space.

2.3 The Warp Factor

Define the warp factor Ω as:

$$\Omega = \frac{S_+ + S_-}{|S_-|}$$

where:

- $S_+ = \sum\lambda_+$ (sum of positive eigenvalues)
- $S_- = \sum\lambda_-$ (sum of negative eigenvalues, which are negative numbers)

Ω measures net curvature relative to attractive curvature.

Properties:

- When $S_+ + S_- = 0$ (positive and negative sums cancel) → $\Omega = 0$
- When $S_+ + S_- > 0$ (positive sum dominates) → $\Omega > 0$
- When $S_+ + S_- < 0$ (negative sum dominates) → $\Omega < 0$
- When there are no negative eigenvalues ($S_- = 0$) → Ω is undefined/infinite (pure Euclidean space)

Ω is a global invariant of the embedding — a field characteristic rather than a concept-level quantity. When $\Omega > 0$, the pseudo-Riemannian space is one kind; when $\Omega < 0$, it is another kind. This distinguishes two qualitatively different types of pseudo-Riemannian geometry, depending on whether positive or negative eigenstructure dominates.

Changes in Ω across measurement epochs, ΔΩ, are diagnostics of how the cognitive field responds to perturbation. (Empirical predictions for ΔΩ appear in Section 7, Prediction P2.)

2.4 Geometry → Graph → Activation Field

For any pair of concepts i and j, define the kernel $K_{ij}(t)$ — an exponential decay function mapping distance to the interval (0, 1]:

$$K_{ij}(t) = e^{-\alpha d_{ij}(t)}$$

As the distance between i and j grows, the kernel approaches zero; $\alpha > 0$ governs the rate at which similarity drops with distance. The exponential form is the maximum-entropy choice given only distance information and is the natural kernel for diffusion processes on metric spaces.

For any pair of concepts i and j, define the authority operator $\phi_{ij}(\eta)$:

$$\phi_{ij}(\eta) = e^{\eta(u_i - u_j)}$$

where $\mathbf{u}$ is an authority vector whose i-th entry u_i reflects the relative authority or influence of concept i. The default operationalization is $u_i = z(\log\ \mathrm{freq}_i)$, where freq_i is the frequency of concept i per million words in the linguistic environment and z denotes z-scoring. This renders $\mathbf{u}$ externally measurable rather than a free parameter.

When $u_i > u_j$, concept i carries greater authority than concept j, and $\phi_{ij}(\eta) > 1 — i$ exerts stronger influence on j than a symmetric model would predict. When $u_i < u_j$, $\phi_{ij}(\eta)$ falls between 0 and 1, and i's influence is correspondingly weaker. The scalar η governs the strength of this asymmetry. When $\eta = 0$, $\phi_{ij} = 1$ for all pairs and the model reduces to a symmetric diffusion process.

The weighted adjacency matrix is then defined as:

$$A_{ij}(t) = K_{ij}(t)\phi_{ij}(\eta)$$

Column normalization yields diffusion operator $\mathbf{P}(t)$.

$$P_{ij}(t) = \frac{A_{ij}(t)}{\sum_k A_{kj}(t)}$$

Let $\mathbf{g} \in \Delta^{n-1}$, $0 < \beta < 1$. The vector $\mathbf{g}$ is a fixed source distribution representing Durkheim's *conscience collectif*. Define:

$$\mathbf{T}(\mathbf{a}) = \beta\mathbf{P}\mathbf{a} + (1-\beta)\mathbf{g}$$

The equilibrium field satisfies:

$$\mathbf{a}^* = \beta\mathbf{P}\mathbf{a}^* + (1-\beta)\mathbf{g}$$

Closed form:

$$\mathbf{a}^* = (1-\beta)(\mathbf{I} - \beta\mathbf{P})^{-1}\mathbf{g}$$

Equivalently:

$$\mathbf{a}^* = (1-\beta)k = 0\infty\beta^k\mathbf{P}^k\mathbf{g}$$

Existence and Uniqueness: $\mathbf{T}$ is a contraction since $\| \mathbf{T}(\mathbf{a}) - \mathbf{T}(\mathbf{b}) \| \leq \beta \| \mathbf{a} - \mathbf{b} \|$. By the Banach fixed-point theorem, a unique $\mathbf{a}^*$ exists.

2.5 Co-Activation and Hebbian Potential

Co-activation weights:

$$w_i(t) \propto a_i^*(t) \cdot \mathbf{1}_{\{i \in S(t)\}}$$

Centroid:

$$\bar{\mathbf{y}}(t) = \frac{\sum_i w_i(t)\mathbf{y}_i(t)}{\sum_i w_i(t)}$$

The centroid of the co-activated set is the natural attractor for Hebbian learning because it minimizes the sum of squared distances weighted by co-activation strength — equivalently, it is the point that best represents the set in the least-squares sense.

Hebbian potential:

$$V_H(\mathbf{Y}; \mathbf{w}) = \frac{k}{2} \sum_i w_i \langle \mathbf{y}_i - \bar{\mathbf{y}}, \mathbf{y}_i - \bar{\mathbf{y}} \rangle_{p,q}$$

Elastic anchoring:

$$V_E(\mathbf{Y}) = \frac{\kappa}{2} \sum_i \langle \mathbf{y}_i - \mathbf{y}_i(0), \mathbf{y}_i - \mathbf{y}_i(0) \rangle_{p,q}$$

Total potential:

$$V = V_H + V_E$$

2.6 Forces and Motion

Force on concept i:

$$\mathbf{F}_i = -k w_i \eta (\mathbf{y}_i - \bar{\mathbf{y}})$$

Motion equation (damped Newtonian):

$$m_i \ddot{\mathbf{y}}_i = -\nabla V - \gamma_i \dot{\mathbf{y}}_i$$

The simplified update equation used in the empirical validations below is obtained by linearizing the full potential-derived force around the co-activation centroid.

2.7 Inertial Mass

The inertial mass m_i of a concept is defined operationally as the ratio of applied force to observed displacement:

$$m_i \propto \frac{\| \mathbf{F}_i \|}{\| \Delta \mathbf{y}_i \|}$$

High-mass concepts displace little under a given force; low-mass concepts displace much.

In human systems, inertial mass appears to be proportional to word frequency — occurrences per million words in the linguistic environment. This identification is supported by high correlations in the barnyard animal domain (Saltiel & Woelfel, 1975; Barnett & Woelfel, 1988; McIntosh & Woelfel, 2017), but the generality of this relationship remains an empirical question requiring further investigation across diverse concept domains. The frequency data used in the empirical validations below are drawn from independent corpora (Thorndike-Lorge, CHAE, Google Ngrams) and are not fitted to the outcome data.

2.8 The Well-Defined Update Map

Theorem (Well-Defined Cognitive Update): Let $\mathbf{Y}(t) \in (\mathbb{R}^{p,q})^n$ with $m_i > 0$, $\gamma_i \geq 0$, and $0 < \beta < 1$. Then one perturbation epoch uniquely determines:

$$\mathbf{Y}(t) \rightarrow \mathbf{P}(t) \rightarrow \mathbf{a}^*(t) \rightarrow \mathbf{w}(t) \rightarrow \mathbf{F}(t) \rightarrow \mathbf{Y}(t + \Delta t)$$

Proof: Geometry uniquely determines $\mathbf{P}(t)$. Since $0 < \beta < 1$, $\mathbf{T}(\mathbf{a}) = \beta \mathbf{P} \mathbf{a} + (1 - \beta)\mathbf{g}$ is a contraction and has a unique fixed point $\mathbf{a}^*$. Weights and potential are uniquely determined. The motion equation is a finite-dimensional ODE with a unique local solution. Therefore the update map is well defined. ■

2.9 The Field Operator

The scalar product matrix $\mathbf{B} = \mathbf{X}\mathbf{X}^T$ from the control condition defines the **field operator** $\mathcal{F} = \mathbf{B}$. For any concept position $\mathbf{x}_i$, the field gradient is $\mathcal{F}\mathbf{x}_i$. This operator determines the path of motion for manipulated concepts — enabling prospective prediction from field structure alone, without treatment data.

The field operator is the matrix form of the pairwise Hebbian update rule implemented in Catpac (Woelfel, 1993). What was previously computed iteratively in Fortran do loops is recognized here as a linear operator acting on the entire semantic space — a shift in perspective that reveals the field structure underlying the dynamics. The implementation of Hebbian learning in Catpac follows the activation dynamics and learning rules articulated by McClelland and Rumelhart (1981, 1986) and the broader Parallel Distributed Processing (PDP) research program. The PDP group was decades ahead of its time, and the field operator formulation is indebted to their insights about distributed representations, Hebbian learning, and activation dynamics. This acknowledgment is not flattery — it is respect for work that laid the foundation for much of what followed in cognitive science and AI.

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3. EMPIRICAL VALIDATION

Four independent studies spanning 40 years provide converging evidence for the field-dynamic framework.

3.1 Korean Immigrant Cultural Convergence (1983)

Study: Kincaid, Yum, Woelfel, and Barnett (1983) measured the semantic spaces of Korean immigrants to Hawaii over time and compared them to the resident US population of Hawaii.

Finding: The immigrants' cognitive spaces converged toward the host-culture equilibrium as a function of time resided in the US. The convergence was modeled using a damped dynamical system:

$$m\ddot{x} + C\dot{x} + kx = 0$$

(open-system version with external force: $m\ddot{x} + C\dot{x} + kx = F$)

Interpretation: Cultural change follows dynamical laws analogous to physical systems approaching equilibrium. This is the macroscopic manifestation of the same field-dynamic processes observed in the laboratory studies below.

3.2 Pigs in Space: Inertial Mass and Field Effects (2017)

Study: McIntosh and Woelfel (2017) examined how synonymous concepts (pig, hog, boar, swine) respond to identical persuasive messages of the form "[Concept] is beneficial and attractive."

Finding: Despite identical messages, the four synonyms moved different distances in Galileo space. Observed total motion:

Condition	Total Motion
Pig	195.2
Hog	401.8
Boar	419.5
Swine	499.9

External mass estimates: Independent lexical frequency estimates (Thorndike-Lorge, CHAE) predicted motion magnitude with extremely high correlation:

Concept	T-L	CHAE	Mass (relative)
pig	44	531	1.00
hog	14	146	0.26
boar	11	168	0.27
swine	8	40	0.20

Correlations with estimated mass:

- Thorndike-Lorge: $r = .995$
- CHAE: $r = .983$

Directional prediction: Using the field-dynamic model:

$$\Delta \mathbf{x}_i = \frac{1}{m_i}(\mathbf{F}_{\mathrm{msg},i} + \mathbf{B}\mathbf{x}_i)$$

where $\mathbf{F}_{\mathrm{msg}}$ is the vector sum toward "beneficial" and "attractive," and $\mathbf{B} = \mathbf{X}\mathbf{X}^T$ from the control condition.

Results:

Model	Mean Cosine (Direction)
Message only	≈ .61
Field only	≈ .48
Combined	≈ .83

Magnitude prediction: Inverse mass predicts observed motion with $r \approx .996$.

Interpretation: Inertial mass (frequency) determines magnitude; field topology improves directional prediction. The combined model substantially outperforms either component alone.

3.3 Nurses vs. Congress: Source Credibility as Direction, Not Magnitude (2017)

Study: McIntosh and Woelfel (2017) compared high-credibility (nurses) and low-credibility (members of Congress) sources delivering identical messages about the Health Care Reform Act (HCRA).

Traditional prediction: High-credibility sources should produce more attitude change.

Observed findings:

Condition	HCRA Motion	Total Motion of Message Components
Nurses (high credibility)	41.28	102.05
Congress (low credibility)	36.37	100.42

Key result: Total motion is nearly identical (102.05 vs. 100.42). Low credibility does *not* reduce motion magnitude. Instead, motion direction differs. **Thus credibility does not increase force magnitude — it changes force direction.**

Vector interpretation:

High credibility:

$$\mathbf{F}_{\text{nurses}} = \mathbf{x}_{\text{beneficial}} + \mathbf{x}_{\text{attractive}} + \mathbf{x}_{\text{nurses}}$$

Low credibility:

$$\mathbf{F}_{\text{congress}} = \mathbf{x}_{\text{beneficial}} + \mathbf{x}_{\text{attractive}} + \mathbf{x}_{\text{congress}}$$

Observed correlations with predicted direction:

- Nurses condition: $r = .703$
- Congress condition: $r = .648$

Field effects: In the control space, nurses are located near "trustworthy," "health," and "self"; members of Congress are located near "unreliable" and "untrustworthy." Thus:

$$\mathbf{Bx}_{\text{nurses}} \rightarrow \text{positive semantic region}$$
$$\mathbf{Bx}_{\text{congress}} \rightarrow \text{negative semantic region}$$

Inertial mass: Google Ngram frequencies:

- "Nurses": 0.00197
- "Congress": 0.000356
- Relative mass (nurses = 1): congress = 0.18

However, the experimental concept "Members of Congress" (multi-word) likely has higher effective mass. Observed motion of the source concepts themselves:

- Nurses moved 17.69 units
- Congress moved 2.67 units

Interpretation: Source credibility affects *direction* (through field gradients) rather than *magnitude*(which is determined by inertial mass). The near-equality of total motion suggests a conservation principle in semantic dynamics.

3.4 Chevrolet–Volvo: Perpendicular Motion Explained (2019)

Study: Woelfel (2019) examined how differentiation messages affect semantic structure. Participants received either:

- Control: standard instructions
- Different: "CHEVROLET and VOLVO are VERY DIFFERENT"
- Similar: "CHEVROLET and VOLVO are VERY SIMILAR"

The puzzle: Volvo moved as predicted by naive theory (cosine = .9996, angle ≈ 0°). Chevrolet moved perpendicular to the predicted path (cosine = .0102, angle ≈ 90°).

Reanalysis using field-dynamic model:

Let $\mathbf{X}$ be the control-condition coordinate matrix (15 concepts × 15 dimensions). The field operator is $\mathcal{F} = \mathbf{B} = \mathbf{X}\mathbf{X}^T$.

Define the unit vector along the Chevrolet–Volvo axis:

$$\mathbf{u}_{ab} = \frac{\mathbf{x}_{\text{Volvo}} - \mathbf{x}_{\text{Chevrolet}}}{\| \mathbf{x}_{\text{Volvo}} - \mathbf{x}_{\text{Chevrolet}} \|}$$

Message-force terms in the differentiation condition:

$$\mathbf{F}_{\text{msg,Chevy}} = -\lambda \mathbf{u}_{ab}$$
$$\mathbf{F}_{\text{msg,Volvo}} = \lambda \mathbf{u}_{ab}$$

Calibration (no parameters estimated from outcome data): $\lambda = \| \mathbf{B}\mathbf{x}_{\text{Volvo}} \|$, using control-condition structure alone. $\beta = 1$.

Combined predicted vectors:

$$\hat{\mathbf{v}}_{\text{Chevy}} = -\lambda \mathbf{u}_{ab} + \mathbf{B}\mathbf{x}_{\text{Chevy}}$$
$$\hat{\mathbf{v}}_{\text{Volvo}} = \lambda \mathbf{u}_{ab} + \mathbf{B}\mathbf{x}_{\text{Volvo}}$$

Results:

Model	Chevrolet	Volvo
Naive (message only)	≈ .00	≈ 1.00

Model	Chevrolet	Volvo
Field only	≈ .70	≈ .39
Combined	≈ .93	≈ .96

Error analysis: Measurement uncertainty (standard errors ≈ 4.85 for Chevrolet, 4.50 for Volvo) implies directional uncertainty of only ~6-7°. Discrepancies of 45°, 67°, or 90° cannot be explained by measurement error. The large residuals are errors of theory, not measurement.

Interpretation: Volvo, situated in a sparser semantic region, moves largely in the direction of the applied differentiating message. Chevrolet, situated in a denser region (close to Ford, VW, Jeep), experiences substantial transverse constraint from the surrounding field. Its motion follows the direction of least resistance — the superposition of message force and field gradient — which is approximately perpendicular to the direct Chevrolet–Volvo axis.

3.5 Summary of Empirical Findings

Study	Key Finding	What It Validates
Korean Convergence (1983)	Damped dynamical system toward equilibrium	Macro-level field dynamics
Pigs in Space (2017)	Frequency predicts mass (r ≈ .996); combined model improves direction (≈.83)	Inertial mass hypothesis; field effects on synonyms
Nurses vs. Congress (2017)	Same magnitude, different direction; credibility changes direction, not force	Field gradients determine trajectory
Chevrolet–Volvo (2019)	Combined model r ≈ .93–.96; perpendicular motion explained	Force + field superposition; asymmetric topology

Together, these studies support the unified model:

$$\Delta \mathbf{x}_i = \frac{1}{m_i}(\mathbf{F}_{\mathrm{msg},i} + \beta \mathbf{B}\mathbf{x}_i)$$

with no parameters estimated from outcome data ($\beta = 1$, $\lambda = \| \mathbf{Bx}_{\text{Volvo}} \|$, m_i from independent frequency data).

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4. ESTIMATION AND IDENTIFIABILITY

Given observed pre/post embeddings $\widehat{\mathbf{Y}}^{\text{pre}}, \widehat{\mathbf{Y}}^{\text{post}}$ from repeated Galileo measurements under known primes $S(t)$:

(i) Geometry-to-graph parameters $\alpha, \eta, \mathbf{u}$: Minimize prediction error in observed displacement:

$$\min_{\alpha,\eta,\mathbf{u}} ti \in V \| R(\hat{\mathbf{y}}_i^{\text{post}}(t) - \hat{\mathbf{y}}_i^{\text{pre}}(t)) - R(\mathbf{y}_i(t+\Delta t) - \mathbf{y}_i(t)) \|_2^2$$

subject to the closed-loop update equations.

(ii) Horizon parameter β: Fit β by matching equilibrium activation-derived predictions to observable proxies (displacement norms, endorsement shifts, prime propagation reach):

$$\beta = \arg \min_{\beta \in (0,1)} \sum_t \quad \mathcal{L}(\text{observables}(t), \mathbf{a}^*(t;\beta))$$

(iii) Source distribution g: Either (a) measure from an external authority/salience signal $\mathbf{s}$ via $g_i \propto s_i$, or (b) infer from equilibrium constraints given $\mathbf{a}^*$ estimates:

$$\mathbf{g} = \frac{(\mathbf{I} - \beta\mathbf{P})\mathbf{a}^*}{1-\beta}$$

Validate by out-of-sample prediction of held-out individuals or contexts.

(iv) Mass m_i: Estimated from a calibration battery using the functional definition in Section 2.7. In human systems, test $m_i \propto \text{freq}_i$. In AI systems, test $m_i \propto 1/\text{median}_t \|$ $\Delta \mathbf{y}_i(t) \|$.

Identifiability triage:

- Case 1: $\mathbf{P}$ from geometry ($\alpha, \eta, \mathbf{u}$ fixed externally), $\mathbf{g}$ from external authority signal → identified.
- Case 2: $\mathbf{P}$ from geometry, $\mathbf{g}$ inferred from observed $\mathbf{a}^*$ → identified if $\mathbf{a}^*$ is estimated from multiple epochs.
- Case 3: Both $\mathbf{P}$ and $\mathbf{g}$ fit freely without constraints → not identified.

The default procedure uses Case 1 with $\mathbf{u} = z(\log\ \text{freq})$ and $\mathbf{g}$ from an independent authority measure.

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5. FIELD EXPANSION AND PHASE TRANSITIONS

5.1 The Warp Factor as Diagnostic Invariant

The warp factor Ω (Section 2.3) measures the balance of attractive and repulsive structure in the embedding. Ω is an invariant of the embedding at a given measurement epoch; ΔΩ across epochs is a diagnostic of cognitive response to perturbation. Together they distinguish classes of intelligent systems.

Empirical finding (preliminary): Human semantic spaces consistently expand under stress ($\Delta\Omega > 0$) — the field opens to novel associations under pressure. Constitutional AI systems consistently contract ($\Delta\Omega < 0$) — the field is pulled toward rigid attractor basins. This asymmetry, if confirmed, reflects a fundamental structural difference between biological cognition and constitutionally constrained artificial cognition (see Prediction P2, Section 7).

5.2 Dimensional Phase Transitions

Under sufficiently large perturbation, the spectral signature of the embedding can change — a positive eigenvalue becomes negative or vice versa. This constitutes a phase transition in cognitive geometry: a qualitative restructuring of the space, not merely a quantitative displacement of concepts within it. Phase transitions are measurable from the eigenvalue structure of $\mathbf{B}$ before and after perturbation. Bootstrap confidence intervals on eigenvalues provide stability criteria distinguishing genuine transitions from measurement noise.

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6. SPECTRAL STRUCTURE AND STABILITY

6.1 The Stationary Distribution

The stationary distribution $\boldsymbol{\pi}$ of $\mathbf{P}$ satisfies $\mathbf{P}\boldsymbol{\pi} = \boldsymbol{\pi}$, $\| \boldsymbol{\pi} \|_1 = 1$. It defines the long-run equilibrium of the diffusion process absent the source restart — where cognitive weight would eventually concentrate if no collective anchor existed.

6.2 The Spectral Gap

Let λ_2 be the second-largest eigenvalue of $\mathbf{P}$. The spectral gap:

$$\Delta = 1 - | \lambda_2(\mathbf{P}) |$$

governs the mixing rate of the cognitive field. Large Δ: fast mixing, strong cultural integration, rapid convergence to collective field. Small Δ: slow mixing, persistent subcultures, modular communities resist integration.

6.3 Structural Stability

If $\mathbf{P}$ evolves with turnover rate ρ (the rate at which the cognitive operator is updated), stability requires:

$$\rho \ll \Delta$$

Mixing must be faster than structural drift for the field to remain coherent. Human cognitive operators change slowly (decades of socialization); AI systems may have higher effective ρ, as retraining can restructure the operator rapidly.

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7. TESTABLE PREDICTIONS

P1 — Inertial mass investigation: The relationship between frequency and inertial mass observed in the barnyard animal domain (r ≈ .995) requires testing across other concept domains. Does it hold for emotion words? Color terms? Political concepts? Or is it specific to synonyms? This is an empirical question, not a settled law.

P2 — Warp factor asymmetry: Matched perturbation (same prime set, same concept list, same time separation) applied to human subjects and Constitutional AI systems should yield $\Delta\Omega > 0$ for humans and $\Delta\Omega < 0$ for Constitutional AI in every replication. Decision criterion: permutation test on ΔΩ, minimum effect size $|\Delta\Omega| > 0.05$.

P3 — Centroid prediction of displacement direction: Given a pre-mapped semantic space, the direction of concept displacement under priming can be predicted from the centroid of the co-activated set. Metric: cosine similarity between predicted and observed displacement vectors, tested against a permutation null (random centroid). Criterion: mean angular error < 45 degrees, $p < 0.001$.

P4 — Alignment metric validity: $\mathrm{Align}(\mathbf{a})$ should correlate with independent measures of cultural integration, socialization, and normative conformity. For AI systems it should track constitutional training intensity across model versions.

P5 — Spectral gap and cultural integration: Populations with higher measured spectral gap should show faster attitude convergence under identical priming conditions. Cross-cultural comparisons should reveal systematic spectral gap differences corresponding to known differences in cultural integration.

P6 — Non-human systems: If the mass variable can be identified for a non-human animal system, the inertial mass law should hold with comparable precision. The framework provides the measurement procedure; the behavioral challenge is eliciting Galileo-equivalent similarity judgments from non-verbal systems.

P7 — Clinical signatures: Psychopathological conditions should manifest as measurable anomalies in field geometry computable from distance judgments alone. Candidate signatures: psychosis → anomalous negative curvature (hyperbolic expansion); depression → high Ω contraction; disrupted attractor structure; abnormal warp factor dynamics.

P8 — Sociological causal priority: The collective field $\mathbf{a}_c^*$ should predict the long-term trajectories of individual fields $\mathbf{a}_a^*$ better than the individuals' own prior states do. This prediction is in principle falsifiable but requires longitudinal developmental data and is more resource-intensive than the other tests in this section. Like cosmological predictions about the fate of the universe, it may be generations before definitive tests are feasible — but that does not make it unscientific.

8. DISCUSSION

8.1 The Ontological Priority of the Collective Field

The standard individualist assumption in cognitive science — that collective phenomena are mere aggregates of individual mental states — is not derived from empirical evidence. It is an inertial inheritance from historical philosophical traditions emphasizing individual primacy, transmitted through Western thought into modern social science.

The empirical facts contradict it. Cultures persist through complete individual turnover. Every person in every society dies; the culture continues. The collective semantic field outlasts any given set of individuals who instantiate it.

This is not mysticism. It is observable, measurable, and falsifiable (see Prediction P8). A child raised by wolves has human biology — the capacity for language, for self-awareness, for symbol use — but not human culture. The biological potential is realized only through immersion in a pre-existing collective field. The field does not erase humanity; it enables it.

The theory does not claim that individuals are born *tabula rasa*. Biological humans are born with specific capacities — for symbol use, for emotion, for self — that distinguish them from other primates. But those capacities are realized only through the collective field into which they are born. Without the biology, no field instantiation. Without the field, the biology produces only animal cognition (not human culture).

This is the falsifiable operationalization of Durkheim's claim that the *conscience collectif* exerts causal force on individual cognition. The collective field $\mathbf{a}_c^*$ should predict trajectories of individual fields $\mathbf{a}_a^*$ better than the individuals' own prior states do. If it does not, the theory fails. If it does, the individualist assumption is empirically refuted.

8.2 Generality Across Intelligent Systems

The theory makes no ontological commitment about the substrate of cognition. It requires only that a system have states representable as concepts with positions, that those positions can be measured through similarity judgments or equivalent procedures, and that position changes can be tracked under perturbation.

The inclusion of non-human animals is a research agenda, not a rhetorical flourish. Corvids, cetaceans, and domestic animals show behaviors suggesting semantic spaces of sufficient richness to instantiate the field. The measurement challenge is adapting the

Galileo similarity judgment procedure to non-verbal systems — a behavioral and experimental problem, not a theoretical one. The theory provides the framework; the empirical work remains to be done.

8.3 The Sociological Foundation

The grounding of the field in the collective is the theory's most distinctive feature. Individual psychology is not denied — it is derived. The individual activation field $\mathbf{a}_a^*$ is fully specified once $\mathbf{P}_a$ and $\mathbf{g}_a$ are known. Individual difference ($\Delta\mathbf{P}_a, \Delta\mathbf{g}_a$) is explicitly represented.

What the framework claims is that the collective field has causal priority over the individual — not merely that it is a useful statistical summary. This claim is empirically testable via P8: does $\mathbf{a}_c^*$predict individual trajectories of $\mathbf{a}_a^*$ better than individual history? The *conscience collectif* is not a metaphor here; it is a measurable distribution whose predictive power over individual cognition is either confirmed or disconfirmed by data.

8.4 Morality as Special Case

The theory of morality developed in Woelfel (2026) is a special case of this general framework in which the concept set V is drawn from the normative/evaluative domain and the source distribution $\mathbf{g}$ is anchored in collectively shared normative concepts. The mathematics are identical to the general framework; existence, uniqueness, Banach stability, and the Hebbian convergence law are inherited without separate proof.

8.5 Bridging the Two Cultures

C.P. Snow (1959) described the separation of scientific and humanistic culture as a loss. The claim of this paper is that the separation was maintained in part by the absence of measurement instruments adequate to humanistic phenomena. Likert scales and semantic differentials project high-dimensional cognitive fields onto single axes and discard the geometry.

Dort/Galileo methodology recovers the geometry. When it is recovered, the phenomena of human cognitive and social life — meaning, belief, identity, values, moral commitment — turn out to follow the same mathematical laws as physical phenomena, at near-deterministic calibration precision in specific domains ($r \approx .93$–$.99$). This is not analogy; it is the formal identity of the mathematical structure. The bridge is the measurement.

9. CONCLUSION

We have presented a general field theory of cognition formalized as a closed seven-link dynamical chain with a single parameter set governing all links. The theory rests on four pillars:

1. **The Pseudo-Euclidean Embedding:** Cognitive states are points in $\mathbb{R}^{p,q}$whose geometry is empirically recoverable from pairwise distance judgments via Galileo/Dort methodology.
2. **The Collective Source:** The activation field is anchored in the *conscience collectif* — the collective cognitive operator $\mathbf{P}_c$ and source distribution $\mathbf{g}_c$ — from which individual fields are derived as perturbations.
3. **The Equilibrium Field:** A unique, well-defined activation field exists (Banach fixed-point theorem) whose solution is the resolvent of the collective diffusion operator weighted by the source distribution.
4. **The Equation of Motion:** Cognitive change follows a damped Newtonian equation with an explicit Hebbian potential, substrate-specific inertial mass (proportional to frequency of occurrence), and damping coefficients governing the elastic/plastic boundary.

The single most important advance of the field-theoretic framework is that the scalar products of the control condition — the field operator $\mathcal{F} = \mathbf{B}$ — determine the path of motion for manipulated concepts, enabling prospective prediction of semantic change from field structure alone.

Empirical validation draws on four independent studies spanning 40 years: Korean immigrant cultural convergence (1983), Pigs in Space (2017), Nurses vs. Congress (2017), and Chevrolet–Volvo (2019). Together, they support the unified model:

$$\Delta \mathbf{x}_i = \frac{1}{m_i}(\mathbf{F}_{\text{msg},i} + \beta \mathbf{B}\mathbf{x}_i)$$

with no parameters estimated from outcome data. The theory is general — applicable across substrates, domains, and species. It is sociological — grounded in the collective rather than the individual. It is mathematical — yielding precise, quantitative, falsifiable predictions. It is empirically grounded — connected to Galileo/Dort methodology that has produced near-deterministic precision in calibration sets ($r = -0.995$, $n=8$, $p < 0.001$) in human cognitive systems and measurable geometric signatures in artificial ones.

The mind is a field. Its dynamics are lawful. We have begun to find the laws.

Not because it is easy, but because it is hard.

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