



Bias as Landscape: The Geometry of Cognition and Evolution

Two-Timescale Geometric Model of Genetic Cognition in Systems Theory: Quantizing Evolutionary Inference and Behavioral Distributions under Genetic, Cognitive, and Environmental Constraint

A. Problem Definition

Human cognition and evolution are typically modeled as fragmented domains: genetic selection as population dynamics, cognitive processes as local adaptation, and behavior as emergent narratives. This separation leaves structural gaps, where evolutionary mechanisms remain disconnected from moment-to-moment intelligence, and genetic bias is treated as background noise rather than foundational geometry. The stakes are high—without a unified substrate, behavioral predictions remain semantically loaded, non-quantifiable, and vulnerable to normative biases, limiting cross-domain integration in systems theory and decision science.

B. Proposed Contribution

We introduce a minimal geometric substrate that unifies genetic optimization, cognitive plasticity, and environmental modulation as movement on a shared manifold. This framework is simpler than existing models by reducing to primitives like fixed wells and frictional costs, more general by spanning timescales from ego probes to generational descent, and reductionist by deriving behavior from biased distributions without semantic content. Its novelty lies in quantizing cognition as sampled trajectories, enabling predictive clustering under constraint.

C. Theoretical Foundations

The model defines cognition as descent over an informational state-space: genetic layer as rigid wells formed by turn-based inference, ego as plastic paths under friction, and environment as anisotropic curvature. Primitives include population-level redistribution (replicator dynamics) and symbiotic modulation (microbiome friction), with relationships governed by asymmetry—deviations toward optima are cheaper than away. This geometry resolves tensions like local vs. global optimization through multi-objective constraints.

D. Cross-Domain Mapping

Constraint topology maps to decision boundaries in systems theory; alignment dynamics to evolutionary inference in behavioral genetics; uncertainty modeling to frictional costs in probabilistic cognition; structural inference to population reweighting in machine learning;

macro-to-micro mapping to two-timescale unification in cognitive architectures; multi-agent incentive geometry to reproductive arity in evolutionary biology; merged trajectory formation to symbiotic modulation in systems biology; recursive strategy formation to genetic cognition in artificial intelligence.

E. Scope and Intent

This work provides a foundational substrate for modeling behavior and evolution, not empirical validation or diagnostics. It excludes moral hierarchies, prescriptive norms, and individual inevitability. The purpose is to define useful structure for future projections in systems theory and decision science.

Conceptual Geometry of Cognition and Evolution

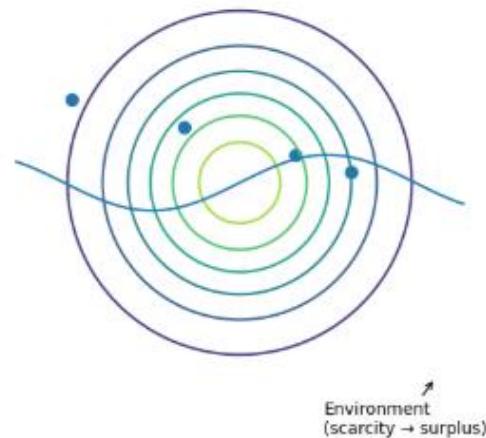


Figure 1. Conceptual Geometry of Cognition and Evolution
High-level schematic of the layered optimization framework. Illustrates nested structural constraints (genetic core to environmental periphery), ego* navigation under frictional cost, population-level redistribution toward genetic attractors across generations, and environmental modulation of landscape curvature (scarcity compressing variance, surplus expanding it). Conceptual geometry only; not to scale.

Keywords Block: informational geometry, genetic cognition, frictional cost, asymmetric friction, low-friction degeneracy, behavioral misalignment, turn-based inference, reproductive arity, persistence gradient, symbiotic modulation, two-timescale unification, constraint topology, scarcity surplus modulation, life history theory, life history strategies, fast-slow continuum, reproductive strategies, mating systems, parental investment, sexual selection, sexual reproduction, reproductive ecology, mating effort, parenting effort, quantity-quality tradeoff, evolutionary demography, alternative reproductive tactics, quantized psychological models, behavioral distribution modeling, quantized cognition, sampled trajectory clustering, predictive behavioral quantization

Orientation Section

This paper proposes a structural substrate for cognition and evolution as a unified geometric model. It is not intended as clinical diagnostics or experimental validation but as a primitive set for deriving higher-order phenomena. The framework provides a foundation for future empirical work, modeling, or cross-domain integration in systems theory. Claims are provisional and reductionist by design, focusing on invariants like fixed optima and frictional costs. The purpose is to define useful structure for behavioral distributions, not to assert perfect truth or normative preference. Terminology is precise but domain-general, with reproduction as the entry primitive for descent logic.

Readers should expect abstraction before application, with extensions (genetic cognition, symbiotic modulators) as optional depths.

Introduction

Across the corpus of modern academic literature, human intelligence has been studied primarily through descriptive and diagnostic lenses. Significant advances have been made through frameworks spanning cognitive psychology, neuroscience, evolutionary biology, and, more recently, computational and statistical learning models. These efforts have produced influential theories—ranging from modular cognition and predictive processing to evolutionary psychology and gene-centered selection—that describe what intelligence appears to do and how it behaves under observation.

In recent decades, a shift has occurred toward incorporating evolutionary concepts into cognitive theory. Notably, the recognition of gene-level selection and self-reinforcing replicative dynamics marked a pivotal realization: cognition is not merely shaped by evolution but may itself function as an evolutionary process. Despite this progress, existing models remain fragmented. Genetic bias, cognitive structure, and evolutionary mechanism are often treated as adjacent domains rather than as a single, continuous system. As a result, the mechanisms of evolution—while internally coherent—remain conceptually disconnected from the moment-to-moment operation of human intelligence.

This work addresses that gap by approaching cognition from a fundamentally different direction. Rather than beginning with high-level cognitive phenomena and abstracting upward, we begin by reducing biology to its most primitive operational mechanism: reproduction. By focusing on reproduction—with sexual recombination as a canonical instantiation—we identify a minimal system governed by constraint, feedback, and variable control. Through this lens, behavior can be modeled, and subsequently quantized, as the outcome of interacting structural pressures rather than emergent narrative traits.

From this foundation, we introduce a geometric theory of cognition. This model describes cognition not as a collection of faculties or functions, but as movement within a constrained state-space defined by informational geometry. Comprehension of the broader evolutionary implications requires engaging this geometric model first. Logical understanding in this framework proceeds by descent rather than ascent: higher-order cognitive and evolutionary behaviors are derived from structural primitives, rather than inferred from surface-level observation.

From this foundation, we introduce a geometric theory of cognition: behavior as movement within a constrained state-space defined by informational geometry. Higher-order phenomena are derived from structural primitives (descent rather than ascent). Only after this geometry is established does the model extend into genetic cognition (Appendix A), where bias, persistence, and selection emerge as formal consequences. Persistent co-regulatory systems (e.g., microbiome) are then integrated as symbiotic friction modulators (Appendix B)

Section 1: Geometric Theory of Cognition

Formalization of the Previously Defined Geometry

Bias as Landscape:

A Layered Model of Genetic Optimization, Cognitive Plasticity, and Behavioral Distributions

1.1. Purpose and Scope:

This paper defines a minimal structural model for understanding how behavior emerges from the interaction of three layers: genetic optimization, cognitive (*ego**) plasticity, and environmental constraint. It is not a theory of morality, identity, pathology, or prescription. It does not assert intent, value, or inevitability at the individual level.

1.2. Its sole claim is structural:

- Biological systems generate biased distributions of behavior rather than free, uniformly likely choices.
- Individual cognition operates within these distributions, navigating a constrained landscape rather than a neutral plane.

This document is written as a foundational substrate. It defines primitives, invariants, and relationships explicitly, without reliance on shared cultural, conversational, or contextual assumptions.

1.3. Definitions and Notation (Clarifying Addendum)

1.3.1. **Persistence:** Persistence denotes the capacity of a behavioral or genetic configuration to reproduce across discrete evolutionary turns. Persistence is not equivalent to instantaneous probability; it requires successful replication across one or more concurrent survivorship channels, depending on the reproductive regime.

1.3.2. **Reproductive Arity:** Let k denote the minimum number of concurrent survivorship instances required for successful propagation. In asexual or mitotic systems, $k = 1$. In sexually reproducing systems, $k \geq 2$, introducing structural co-dependence without altering the underlying evolutionary geometry.

1.3.3. **Ego*** denotes self-aware cognitive autonomy operating within biological, reflexive, microbial, and environmental constraints. Ego* does not imply continuous deliberative control; most behavior is executed autonomously once trained, with strategic cognition engaged episodically under uncertainty or conflict.

1.4. Core Claim: Behavior is not generated ex nihilo by choice. It is sampled.

At the population level, biological structure defines a mean and variance envelope for behavior. At the individual level, cognition selects trajectories within that envelope under frictional cost. Environmental conditions modulate curvature and variance without altering underlying structure.

In short: There is no unbiased behavior—only variance around a mean.

This model predicts the geometry of behavioral distributions, not the semantic content of the behaviors themselves.

1.5. Layer I: The Genetic Optimization Surface

1.5.1. Definition:

The genetic layer is defined as a rigid, non-learning, non-self-orienting system. It consists of a finite, well-documented set of viable configurations that persist across generations. Genes do not update incrementally, acquire information within a lifetime, or optimize locally. They persist through replication.

Time in this layer advances discretely. One generation constitutes one turn. Each turn redistributes population mass across a static fitness landscape.

1.5.2. Static Landscape, Dynamic Distribution

Across generations, the genetic layer performs population-level inference. Each generation constitutes a discrete turn in which genotype-encoded strategies are executed under environmental constraints. Differential survival and reproduction reweight population mass toward higher-fitness basins. No intent is modeled within a single organism's lifetime; inference emerges only through repeated population-level filtering across turns.

The genetic fitness landscape is fixed. It contains a limited configuration space, one or more global optima, and defined gradients of viability. What changes across generations is not the landscape, but the distribution of variants within a population.

Thus, evolution is not modeled as a changing function, but as a sequence of redistributions: a static surface and a moving probability mass.

In sexually reproducing systems, persistence is relational rather than unary, producing structured bias that cannot be reduced to independent probability events (see *Reproductive Arity, Definitions*).

Environmental conditions vary on organismal timescales and modulate host behavior and realized fitness, but they do not alter the underlying genetic configuration space across a single evolutionary turn. Environmental change acts through host bodies within turns; genetic combinatorics update only across turns.

1.5.3. Bias as Distribution

The genetic layer does not impose outcomes on individuals. It produces a population-level probability cloud with a mean, variance, and attractors under constraint. This bias is survivorship-weighted, not intentional. The resulting distribution need not be normal; it may be skewed, multimodal, or heavy-tailed depending on environmental curvature and constraint anisotropy.

1.6. Layer II: *Ego** as a Plastic Local Optimizer

1.6.1. Definition

The *ego** is the cognitive system responsible for simulation, inhibition, delayed gratification, and local optimization under constraint. Unlike genes, the *ego** learns, adapts, can resist gradients, and operates continuously rather than discretely.

*Ego** functions as a supervisory optimizer capable of simulation, inhibition, and delayed local optimization under constraint.

*ego** denotes episodic, defeasible supervisory cognitive autonomy operating within multilayered biological, reflexive, microbial, symbiotic, and environmental constraints on a shared informational manifold. It is the plastic local optimizer responsible for simulation, inhibition, delayed optimization, and trajectory sampling under frictional cost.

Important clarification: The term "ego" (marked here with an asterisk) is not being used in the Freudian psychoanalytic sense (i.e., the rational mediator among id, ego, and superego in a tripartite psyche), nor in any related ego-psychological, narrative-self, or moral-agency tradition. The asterisk signals complete dissociation from those usages. For the full contrast, rationale, and semiotic justification of reusing the term as an optimal hinge to pre-existing contexts of conscious cognition, see Appendix E: Clarification on ego Terminology and Semiotic Hinge.

1.6.2. Frictional Cost

Movement against genetic gradients is possible but not free. Resistance incurs frictional cost experienced cognitively, emotionally, or physiologically. This cost increases with distance from the genetic mean, is modulated by development and plasticity, and generally increases as neural structures ossify with age.

1.6.3. Local vs. Global Optimization

The *ego** optimizes locally and temporally, while genetic optimization is global and population-level. A behavior may be *ego*-optimal* but genetically suboptimal, and vice versa. This tension is structural, not pathological.

1.7. Layer III: Environment as Curvature

The environment modulates the landscape without altering its fundamental structure. Scarcity, competition, stress, and surplus affect gradient steepness, variance width, and the cost of deviation. Scarcity compresses distributions; luxury expands variance. Environmental modulation is anisotropic across behavioral dimensions.

1.8. Composite Geometry

The interaction of the three layers produces a high-dimensional surface. Genetic structure defines fixed wells, *ego** navigation traces paths across surfaces, and the environment tilts curvature. Behavioral attractors emerge where bias is strong, friction is low, and constraints align. Outliers occupy the tails of the distribution.

1.9. Sex as a Canonical Stress Test (Non-Normative)

Sexual behavior is used as a canonical example due to steep genetic gradients, high signal-to-noise, and extensive biological documentation. It is not treated as morally privileged or prescriptive. The model predicts clustering, variance, and friction without appealing to intent.

Sexual reproduction is not merely an example but the canonical instantiation of genetic time, defining both the terminus of one evolutionary turn and the origin of the next.

This paper functions as a substrate beneath prior frameworks, grounding them rather than replacing them.

1.10. Relationship to Prior Work

Explicit Non-Claims:

This model does not claim individual inevitability, moral hierarchy, intentional design, prescriptive norms, or diagnostic sufficiency. It claims only that structure precedes choice.

Conclusion

This paper builds directly on *Toward a Structural Model of Relationship Compatibility*, which introduced a non-normative, geometric treatment of compatibility as constrained alignment within a biased space rather than as preference, intent, or identity.

The present work generalizes that framework by extending the notion of structural bias downward to its biological substrate. Where the prior model analyzed compatibility and friction at the relational and behavioral level, this paper formalizes the genetic, cognitive, and environmental geometry that produces such distributions in the first place.

The relationship compatibility model can therefore be understood as a specific instantiation of the broader optimization landscape defined here, operating at a higher descriptive layer without revising the underlying geometry.

1.11. Conclusion:

Human behavior emerges from biased landscapes navigated by plastic cognition under constraint. Genes define means, not mandates. *Ego** selects paths, not planes. Environment shapes curvature, not structure.

Understanding behavior therefore requires modeling distributions rather than debating exceptions. This paper defines the minimal primitives necessary to do so.

Section 2: Mathematical Formalization of the Gene–*Ego** Optimization Landscape

2.1. State Spaces

We define two orthogonal but interacting spaces.

2.1.1 Genetic State Space \mathcal{G}

Let

$$\mathcal{G} = \{g_1, g_2, \dots, g_n\}$$

Where:

- Each g_i is a genetically realizable configuration
- \mathcal{G} finite, discrete, and fixed
- No element of \mathcal{G} self-orient or adapts during an organism's lifetime

There exists a subset:

$$\mathcal{G}^* \subset \mathcal{G}$$

Such that:

- \mathcal{G}^* represents genetically successful configurations
- For sexual reproduction, $|\mathcal{G}^*| \ll |\mathcal{G}|$
- In the simplest model, $|\mathcal{G}^*| = 1$

2.2. Genetic Fitness Function

Define a population-level fitness function:

$$F_g: \mathcal{G} \rightarrow \mathbb{R} \geq 0$$

Properties:

- F_g is maximized at \mathcal{G}^*
- F_g is radially decreasing as distance from \mathcal{G}^* increases
- Distance is *topological*, not moral or semantic

We can model this as a potential well:

$$F_g(g) = \exp(-\alpha \cdot d(g, \mathcal{G}^*))$$

Where:

- $d(\cdot)$ is a metric over genetic configurations
- α controls selection pressure

This encodes genetic bias without implying intent.

2.3. *Ego** State Space \mathcal{E}

Define:

$$\mathcal{E} \subset \mathbb{R}^k$$

Where:

- \mathcal{E} is continuous
- Dimensions encode learned preferences, norms, abstractions, suppressions
- k varies across individuals and environments

Unlike \mathcal{G} :

- \mathcal{E} is plastic
 - Plasticity $\partial\mathcal{E}/\partial t$ decreases with age
 - Learning cost is non-linear
-

2.4. *Ego** Utility Function

Define:

$$U_e: \mathcal{E} \times \mathcal{G} \times \Xi \rightarrow \mathbb{R}$$

Key properties:

- *Ego** utility may increase away from genetic optimum
- *Ego** utility is contextual (environmental, social, symbolic)
- *Ego** utility is locally optimized, not globally

This formalizes the claim that *ego** optima may exist anywhere on the well.

2.5. Friction Function (Core Insight)

Define friction as the cost of deviation between *ego** and genetic optima:

$$\Phi(e, g) = \beta \cdot d(g, \mathcal{G}^*) \cdot C(e)$$

Where:

- $C(e)$ is cognitive cost
- β is environmental modulation (scarcity vs surplus)

Properties:

- Friction increases monotonically with genetic deviation
- Friction is experienced subjectively but generated structurally
- Friction is asymmetric: some deviations are costlier than others
- Specifically, deviations toward the genetic optimum are cheaper than deviations away, reflecting selection pressure favoring return to the mean.

The friction function is typically asymmetric. Deviations toward genetically successful configurations are less costly to persist than deviations away, reflecting biological constraint, repair pressure, and survivorship bias accumulated across evolutionary turns. This asymmetry reflects selection pressure

favoring return to the mean, but does not imply optimality, deliberative intent, or teleology at any level of the system.

! Note: No assumption is made regarding flatness, symmetry, or isotropy of the genetic surface. Friction is defined relative to local geometry: deviation costs may arise from slope, curvature, anisotropy, or constraint density. The model requires only that resistance to deviation exists; its precise directional form is left unspecified.

Although exponential and concentration forms are used, no stochastic process, sampling assumption, or Gaussian structure is implied. The geometry defined here is deterministic and constraint-driven; population-level concentration arises from turn-based persistence under reproduction, not probabilistic inference.

2.6. Combined Optimization Surface

Define a total utility function:

$$U_{total}(e, g) = U_e(e, g) - \Phi(e, g)$$

This yields:

A high-dimensional surface

With:

- A fixed genetic attractor
- A mobile *ego** optimum
- Environmentally modulated curvature

This surface:

- Is not symmetric
 - Is not smooth everywhere
 - Contains local maxima for the *ego**
 - Contains a global maximum for genes (population-level)
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2.7. Population-Level Distribution

Across a population P , the distribution over genetic configurations is a Boltzmann-weighted concentration around the genetically successful set G^* :

$$P(g) = \frac{1}{Z} \exp\left(-\frac{1}{2} d(g, G^*)^\top G_g d(g, G^*)\right)$$

Where:

$$d(g, G^*) = \min_{g^* \in G^*} d(g, g^*).$$

This form defines a survivorship-weighting kernel over a discrete configuration space. The exponential

encodes monotonic survivorship decay under constraint; it does not imply probabilistic inference, Gaussian structure, or statistical estimation.

The operator \mathcal{G}_g encodes direction-dependent curvature and concentration rather than statistical covariance.

Dispersion and anisotropy of this concentration are governed by:

- environmental variance,
- developmental noise,
- and constraint relaxation under surplus.

Individuals do not choose this distribution.

They instantiate samples from it.

Genetic Geometry Operator

Definition.

Let \mathcal{G}_g denote a fixed geometric weighting operator over the genetic configuration space \mathcal{G} .

\mathcal{G}_g encodes directional constraint and anisotropy arising from biological feasibility, developmental coupling, and reproductive compatibility.

\mathcal{G}_g is structural, not statistical:

- It is not a covariance matrix
- It is not inferred or estimated from data
- It does not represent noise, uncertainty, or variance
- It does not imply Gaussian structure
- \mathcal{G}_g need not be invertible, symmetric, or positive-definite; it encodes constraint, not measurement geometry.

\mathcal{G}_g is fixed across generations and acts only to weight displacement from genetically successful configurations \mathcal{G}^* .

⚠ Note: Although exponential forms and quadratic distance terms appear in the population-level distribution, this model does not invoke statistical inference, probabilistic sampling, Gaussian assumptions, or estimation theory. The Boltzmann-like expression is used strictly as a survivorship-weighting kernel over a finite, discrete configuration space, encoding monotonic persistence decay under constraint rather than uncertainty, noise, or belief updating. The operator \mathcal{G}_g is not a covariance matrix, is not inferred from data, and need not be symmetric, invertible, or positive-definite; it represents directional biological constraint and feasibility, not statistical variance. No claims are made regarding normality, likelihood, entropy maximization, or stochastic optimality. Individuals are not modeled as draws from a probability distribution in an epistemic sense; they instantiate configurations shaped by turn-based survivorship filtering. Any resemblance to statistical mechanics or Bayesian formalisms is structural and not inferential, reflecting shared geometry rather than shared semantics.

2.8. Evolution as Turn-Based Redistribution

Let t index generations, not individuals.

Then:

$$P_{t+1}(g) = \mathcal{R}(P_t(g), F_g)$$

Where:

- \mathcal{R} is a selection-and-replication operator
- No g mutates *itself*
- Orientation emerges only across turns

Genes do not advance.

Distributions sharpen or diffuse.

2.9. Key Constraints (Explicit)

1. Genetic space is finite
 2. Genetic fitness landscape is fixed
 3. *Ego** landscape is plastic but costly
 4. Optimization is multi-objective and asymmetric
 5. Bias is unavoidable
 6. Neutrality does not exist
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This slow inference process discovers the wells that the main model treats as fixed optima. *Ego**, operating on the same manifold, probes those wells within lifetimes at frictional cost.

Section 3: A General Theory of Evolution

3.1. Genetic Cognition as Turn-Based Inference

While the primary model describes individual cognition as local optimization over a constrained manifold, it also reveals a slower, population-level form of cognition embedded in genetics.

The emergent survivorship bias produced by this turn-based redistribution is denoted G_{ego^*} : a population-level persistence gradient arising from replication constraints rather than deliberation or representation.

A genotype can be treated as a policy proposal: a compact model of how to act and build in a world with specific regularities. Each generation executes these policies as rollouts in the environment. Survival and reproduction score these policies, and the population distribution updates accordingly.

This process is non-deliberative yet algorithmic: a turn-based inference loop that compresses environmental structure into heritable constraint. This is genetic cognition.

Ego^{}* is the fast optimizer.

Genes are the slow optimizer.

Environment supplies curriculum and curvature for both.

3.2. Mathematical Bridge to Evolutionary Dynamics

Let $p_t(g)$ denote the population distribution at generation t .

Replicator Update (Selection Only)

$$p_t + 1(g) = \frac{p_t(g)W(g; \mathcal{E}_t)}{\sum_{g'} p_t(g')W(g'; \mathcal{E}_t)}$$

Replicator–Mutator (Selection + Exploration)

$$p_t + 1(g') = \frac{\sum_g p_t(g) W(g; \mathcal{E}_t) Q(g \rightarrow g')}{\sum_h p_t(h) W(h; \mathcal{E}_t)}$$

Where Q encodes mutation and recombination.

3.3. Interpretation

- Curvature: Hessian of $\log W(g; \mathcal{E})$ determines variance
- Friction: deviation cost maps to effective selection penalty
- Timescales: ego^* optimizes continuously; genes optimize discretely

Evolution is Bayesian-like reweighting:

$$p_{t+1}(g) \propto p_t(g) \cdot W(g; \mathcal{E}_t)$$

Evolution is turn-based cognitive descent on a shared manifold.

Section 4: Microbiome as Symbiotic Friction Modulator

While the model focuses on genetics, *ego*^{*}, and environment, symbiotic systems within the host introduce additional non-voluntary influences.

The microbiome represents a distributed microbial ecosystem that modulates cognition via metabolites, neurotransmitters, and immune signaling. It does not learn deliberatively, nor does it constitute a fourth optimization layer.

Instead, it introduces a lesser but structurally meaningful friction term.

4.1. Integration with the Model

- Acts within *ego*^{*} and environmental layers
- Modulates baseline affect, stress response, and decision cost
- Is downstream of genetics and environment

Formally:

$$\Phi_{sym} = \gamma \cdot M(h)$$

Where

$$\gamma < \beta$$

This resolves residual variance in *ego*^{*} friction without altering the core geometry.

Full quantification of microbiome effects remains an open area for extension and is beyond the scope of this substrate.

4.2. Reproduction as the Temporal Primitive

In this framework, we introduce the concept of genetic (genomic) time, in which reproduction is the lowest-level primitive that instantiates change in the unit of time. Genetic state does not advance continuously; it advances as a step function, updating only when a reproductive event occurs. In sexually reproducing systems, this event is the mating interaction (sex), which is therefore a behavioral act that defines the discrete “tick” of evolutionary time.

Crucially, not all reproductive acts advance genetic time. Only those interactions that result in viable offspring instantiate a state update; unsuccessful or non-viable matings incur behavioral and energetic cost without advancing the genetic index. This distinction formalizes reproduction as a necessary but not sufficient condition for temporal progression in genetic space.

Associative Reinforcement and Misalignment

Because chemical reward is delivered at the ego* and G_{ego^*} interfaces independently of successful advancement of genetic time, repeated mating-associated reward can become associatively bound to incidental contextual features co-present during the act. Over sufficient repetition, these features may acquire incentive salience through basic reinforcement dynamics, even when they are orthogonal or negatively aligned with reproductive success.

As a result, the behavioral system may stabilize around non-optimal or non-reproductive attractors—that is, regions of the state space that reliably trigger reward despite failing to advance $t \rightarrow t+1$. This does not represent dysfunction, preference, or intent; it is a consequence of Pavlovian reinforcement acting on a reward signal that is correlated with, but not contingent upon, genetic update. Such reinforcement can therefore hard-code attraction toward arbitrary stimuli that happen to co-occur with low-friction reward delivery, regardless of their relationship to genetic optimization.

4.3. Degeneracy Under Low-Friction Regimes

In sufficiently low-friction environments, ego* policies may traverse wide regions of the behavioral manifold without incurring corrective cost. When environmental, energetic, or genetic constraints are shallow or delayed, local reward signals dominate action selection, even when those actions are weakly coupled—or uncoupled—from long-horizon survivorship outcomes.

From the perspective of the organism–environment system, such regimes constitute a degeneratively biased state. Here, degeneration is not pathological or normative; it is geometric. Constraint gradients flatten relative to the magnitude and immediacy of chemically mediated reward, reducing the informational curvature available for corrective descent toward genetically successful attractors. Multiple behavioral trajectories become effectively reward-equivalent despite differing contributions to long-term persistence.

In these conditions, Pavlovian reinforcement mechanisms may stabilize locally optimal but globally misaligned behaviors. Because reward delivery at the ego* and G_{ego^*} interfaces is not strictly contingent on advancement of genetic time $t \rightarrow t+1$, repeated low-cost reinforcement can bind incentive salience to incidental or symbolic features of the environment. Over sufficient repetition, these features may acquire behavioral priority independent of their relationship to reproductive success or environmental resilience.

At the population level, prolonged exposure to low-friction regimes can bias the frequency of organismal variants toward such misaligned attractors. This shift does not imply dysfunction, error, preference, or intent. It is a structural consequence of optimization operating under reduced constraint curvature: when corrective gradients are weak, exploration dominates, and reinforcement consolidates whatever trajectories are locally stable.

Thus, degeneracy in this framework denotes a loss of gradient discrimination rather than a loss of function. The system continues to optimize, but does so under impoverished geometric

guidance, allowing behavior to drift away from genetic optima while remaining internally coherent and chemically reinforced.

Appendix A: Definitions and Scope Constraints

A.1 Purpose

This appendix stabilizes terminology without modifying structure or claims.

No term in this paper should be read as implying:

- moral agency
 - teleology
 - conscious design
 - normative preference
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A.2 Genetic Optimization (Non-Intentional)

Genes persist or vanish via replication across discrete generations.

Any apparent directionality arises from redistribution, not intent.

A.2a Genetic Ego^* (\mathcal{G}_{ego^*})

\mathcal{G}_{ego^*} denotes the population-level survivorship bias that emerges across evolutionary turns from replication constraints, including reproductive arity. It does not imply deliberative intent, representation, or agency within a single organism's lifetime. \mathcal{G}_{ego^*} is an emergent statistical property of turn-based persistence: configurations that repeatedly satisfy survivorship requirements accumulate population mass over time.

\mathcal{G}_{ego^*} is not an operator on \mathcal{G} and should not be confused with \mathcal{G}_g ; it denotes an emergent population-level persistence gradient rather than a geometric weighting kernel.

In sexually reproducing systems, \mathcal{G}_{ego^*} reflects relational persistence rather than unary probability, as successful propagation requires coordinated survivorship across multiple instances. In asexual systems, \mathcal{G} reduces to unary persistence. These regimes are parallel expressions of the same turn-based optimization geometry.

A.3 Ego*: Cognitive Autonomy Under Constraint

Ego* denotes supervisory cognition capable of simulation, inhibition, and delayed optimization under constraint. (as defined in Section 1)

A.4 Limits of ego^* Autonomy

Ego* is episodic, not continuous.

Execution subsystems perform most behavior once trained.

A.5 Ego* vs. Execution Subsystems

Strategy vs. execution resolves autonomy-reflex tension.

A.6 Parallel Genetic Systems

Microbial systems are parallel optimizers acting only through friction modulation.

A.7 Timescale Stratification

System	Update Mode	Timescale
Ego*	Continuous	Seconds–years
Microbes	Turn-based	Hours–days
Organism	Developmental	Decades
Genes	Turn-based	Generations

A.8 Intent and Semiotics

Optimization language is descriptive, not teleological.

Appendix B: Canonical Symbols and Operators

Purpose:

This appendix defines the canonical meaning, type, and domain of all formal symbols used in the manuscript. It serves as a semantic checksum to prevent reinterpretation across sections or inference contexts.

B.1 State Spaces

- \mathcal{G} — Finite, discrete genetic state space
Type: set
Mutability: fixed
- $\mathcal{G}^* \subset \mathcal{G}$ — Subset of genetically successful configurations
Type: set (possibly singleton)
- \mathcal{E} — Continuous *ego*^{*} state space
Type: manifold / vector space

B.2 Functions

- $F_g : \mathcal{G} \rightarrow \mathbb{R}_{\geq 0}$ — Genetic fitness function
Scope: population-level
Intent: non-teleological
- $U_e : \mathcal{E} \times \mathcal{G} \times \Xi \rightarrow \mathbb{R}$ — *Ego*^{*} utility function
Scope: individual, contextual
- $\Phi(e, g)$ — Friction (deviation cost) function

B.3 Parameters

- α — Selection pressure constant
- β — Environmental modulation coefficient
- γ — Symbiotic (microbial) friction coefficient
Constraint: $\gamma < \beta$

B.4 Operators and Metrics

- $d(\cdot)$ — Topological distance metric over \mathcal{G}
Explicitly non-semantic, non-moral
- $R(\cdot)$ — Selection–replication operator

B.5 Distributions

- $P(g)$ — Population-level distribution over \mathcal{G}
 - $p_t(g)$ — Distribution at generation t
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Appendix C: Layered Optimization Stack

- Genetics defines structure
 - *Ego** enables conditional autonomy
 - Environment modulates curvature
 - Behavior is biased sampling
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C.1 Layer Optimized Stack

Biological behavior arises from a layered optimization stack operating across distinct time scales and substrates. These layers do not share agency, intent, or representational capacity, but they jointly shape the feasible action space of the organism. Cognitive autonomy (*ego**) is emergent and defeasible: it can be biased, overridden, or voluntarily relinquished by lower layers without being eliminated. No layer is sufficient alone; behavior is always the composite projection of all active layers under constraint.

Layer Substrate	Time Scale	Control Mode	Optimization Type
L1 Genetic substrate	(10^3 – 10^9) years	None (structural)	Survivorship filtering
L2 Microbiome ecology	hours–days	Chemical bias	Rapid fitness modulation
L3 Reflex & conditioned programs	ms–seconds	Override-capable	Trained / hardwired responses
L4 Ego* (cognitive autonomy)	seconds–years	Partial, defeasible	Strategy & planning
L5 Social / memetic field (Culture, norms, institutions)	Generations	External constraint	Cultural selection

Lower layers bias or override behavior through structural or programmatic mechanisms; higher layers act by shaping the decision surface available to cognitive autonomy rather than directly executing action.

- L1–L3 operate *within* the organism
- L4 is emergent autonomy (*ego**)
- L5 is externalized cognition (culture, norms, language)

Reflex demonstrates that *ego** is not complete agency

C.2 Extended Constraint Stack

Layer System	Optimization Mode	Learns?	Acts on
1 Genetics	Turn-based, population	✗	Structure
2 Microbiome / Symbionts	Turn-based, fast	✗	Friction
3 Developmental / Reflex	Deterministic	✗	Execution
4 Ego*	Continuous, local	✓	Trajectories
5 Environment	External curvature	✗	Cost surface

Key asymmetry:

- Layers 1–3 do not choose
- Layer 4 navigates
- Layer 5 constrains everything but optimizes nothing

This is why microbiome + reflexes are not “just more cognition” — they *pre-shape the cost function*

Microbial and reflexive systems modify Φ but do not introduce new optima.

Appendix D: Definitions

This sections serves as a notational checksum and definitional consolidation

D.1 Sets and State Spaces

- \mathcal{G} — Genetic configuration space
Type: finite, discrete space
Elements: $g \in \mathcal{G}$
Mutability: fixed across generations
- g — A genetic configuration
Type: element of \mathcal{G}
- $G * \subset \mathcal{G}$ — Genetically successful configuration set

⚠ Note: \mathcal{G} is never indexed; only operators are.

D.2 Functions and Operators

- $d(g_1, g_2)$ — Distance function over \mathcal{G}
Role: measures deviation between genetic configurations
Not: statistical metric unless explicitly stated
- \mathcal{G} — Genetic geometry operator evaluated at configuration g
Domain: tangent structure over \mathcal{G}
Role: encodes direction-dependent biological constraint and survivorship cost
Not: covariance matrix, estimator, or noise model
- Z — Normalization constant ensuring finite total mass
Role: scaling only; no probabilistic interpretation

D.3 Emergent Fields and Biases

- \mathcal{G}_{ego^*} — Emergent ego^* * survivorship bias
Type: population-level field over cognitive state space
Arises from: repeated replication under constraint
Not: an operator on \mathcal{G} ; not indexed by g

D.4 Parameters and Coefficients

- α — Selection pressure
- β — Environmental modulation coefficient
- γ — Symbiotic friction coefficient ($\gamma < \beta$)
Optional but useful:
 - Units or qualitative scale (low / high)

Notation Invariant.

Calligraphic symbols (\mathcal{G}, \mathcal{E}) denote spaces or induced geometries.

Lowercase roman symbols (g, e) denote elements of those spaces.

Subscripts index evaluation, not redefinition.

Here's the clean semantic stack:

- g — a concrete genetic configuration (instance)
- \mathcal{G} — genetic configuration space / geometry
- \mathcal{G}^* — genetically successful subset / attractor set
- \mathcal{G}_g — geometry-weighting operator indexed by configuration g
- \mathcal{G}_{ego^*} — genetic constraint geometry acting on ego* expressions

And in parallel:

- e — an environmental or experiential state
- \mathcal{E} — environmental / constraint space
- \mathcal{E}_{ego^*} — ego*-relevant environmental geometry

⚠ Note: Ego notation constraint.

All formal references to cognitive autonomy use the symbol ego^* .

The asterisk denotes episodic, defeasible autonomy operating under structural constraint.

The symbol **ego** without an asterisk is not used in formal expressions.

Ξ — Contextual constraint space

Type: external, non-agentic parameter space

Role: conditions ego^* utility evaluation via social, symbolic, and institutional context

Learns: ✗

Optimizes: ✗

Acts: ✗

⚠ Note: Ξ modulates U_e but does not introduce optima or dynamics of its own.

Appendix E: Clarification on ego Terminology and Semiotic Hinge*

Clarification on ego Terminology and Semiotic Hinge

ego* denotes episodic, defeasible supervisory cognitive autonomy operating within multilayered biological, reflexive, microbial, symbiotic, and environmental constraints on a shared informational manifold. It functions as the plastic local optimizer capable of simulation, inhibition, delayed gratification, trajectory sampling, and local optimization under frictional cost—navigating genetic attractors and environmentally modulated curvature without continuous deliberative control.

Most behavioral execution occurs autonomously via trained subsystems once policies are instantiated; ego* engages strategically and intermittently, primarily under conditions of uncertainty, conflict, high cost, or gradient misalignment.

This usage of "ego" (marked by the asterisk) is not the ego in the Freudian psychoanalytic sense. In Freud's structural model, the ego is the rational, reality-oriented mediator within a tripartite psyche: it balances the instinctual, pleasure-seeking drives of the id; the moralistic, internalized prohibitions and ideals of the superego; and the demands of external reality. The Freudian ego operates according to the reality principle, employs defense mechanisms to manage intrapsychic conflict, maintains continuity of self through memory and anticipation, and serves as the integrative executive reconciling these forces while preserving self-preservation and adaptive functioning. It is fundamentally a site of conscious reason, common sense, moral negotiation, and reality testing, embedded in a dynamic of unconscious conflict and repression.

In contrast, ego* in this framework carries no implication of:

- tripartite psychic structure (id/ego/superego),
- moral agency, teleology, or prescriptive norms,
- defense mechanisms, repression, or intrapsychic conflict resolution,
- continuous conscious selfhood or the experiential "I" as primary organizer,
- intentional mediation between unconscious drives and societal morality.

ego* is a purely structural and geometric primitive: a supervisory navigator on a constrained optimization landscape, where "autonomy" is episodic and defeasible (overridable by lower-layer gradients, reflexive circuits, symbiotic modulation, or environmental curvature), and "self-awareness" refers only to capacity for meta-simulation within the manifold, not to any phenomenological or narrative self.

The deliberate choice to adopt and adapt the term "ego" (rather than coin entirely novel notation such as "supervisor," "meta-optimizer," or "trajectory selector") serves as an optimal semiotic hinge. It anchors the model to deep pre-existing cultural and scientific context specific to conscious cognition—leveraging centuries of discourse around the "I," rational control, self-reference, and executive function (from Freud through ego psychology to modern cognitive science, neuroscience, and discussions of self-regulation). This hinge facilitates rapid cross-domain intelligibility and dialogue: readers already familiar with terms like "ego

functions," "ego strength," "ego depletion," or even colloquial "ego" (self-control, self-importance) can map onto the geometric substrate with minimal onboarding cost, while being immediately and explicitly disabused of imported psychoanalytic or normative baggage. The asterisk ensures the reuse remains precise and non-confusing, turning a potential point of misreading into a bridge for broader accessibility.

 Note: This appendix does not modify any claims in the main text; it exists solely to stabilize interpretation and prevent semantic leakage from prior traditions.

Appendix F: License and Usage Details

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