

A Cross-Domain Entropy Model of Discernment: Semantic Essence, Physiological Coherence, and the Necessity of an Independent Invariant.

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Abstract

Discernment—the ability to extract stable meaning from ambiguous, noisy, or conflicting information—has no formal quantitative definition in psychology. We propose a cross-domain entropy model in which discernment arises when semantic entropy and physiological entropy converge toward a shared attractor. Semantic essence is defined as the low-entropy invariant that emerges across paraphrases, embeddings, and contextual perturbations. Physiological coherence is operationalized through autonomic stability, measurable via heart-rate variability (HRV). We introduce the *Discernment Index* (DI), a normalized metric combining semantic stability, autonomic entropy, and contextual divergence. Simulations demonstrate how semantic noise and physiological instability jointly reduce DI, while empirical paradigms are proposed to validate the model through semantic stability judgments coupled with HRV recording. This framework unifies information theory, predictive processing, autonomic neuroscience, and modern embedding models into a publishable mathematical psychology formulation of discernment.

Introduction

Discernment traditionally refers to a person’s ability to “see clearly” through ambiguity, deception, or internal conflict. Although intuitively understood, it remains one of psychology’s least formalized constructs. No agreed-upon mathematical definition exists, and empirical measures are fragmentary at best. What is missing is a principled account of how humans extract stable meaning when both language and physiology are noisy, dynamic, and unreliable.

Information theory provides one relevant foundation. Shannon’s (1948) treatment of uncertainty through entropy offers a quantitative way of modeling meaning degradation under noise. Extensions by Jaynes (1957) and Cover and Thomas (2006) demonstrate how entropy, covariance, and divergence govern stability in high-dimensional systems. Yet psychological meaning is not purely linguistic—it is embodied. Predictive processing accounts (Clark, 2013; Hohwy, 2013), with deep roots in free-energy minimization (Friston, 2010), show how the nervous system continuously reduces uncertainty by aligning internal models with incoming data. The autonomic nervous system participates in this process: stable HRV signatures correlate with improved executive function, clarity, and emotional regulation (Thayer & Lane, 2000; Shaffer & Ginsberg, 2017).

Modern semantic models similarly reveal that meaning can be approximated as low-entropy attractors in embedding space. Across paraphrases, embeddings cluster into stable “essence”

vectors (Mikolov et al., 2013; Pennington et al., 2014; Devlin et al., 2019). When embeddings disperse, interpretations diverge. When they converge, essence becomes computationally identifiable.

Despite these advances, psychological science lacks an integrated framework linking:

1. Semantic stability (linguistic entropy)
2. Autonomic stability (physiological entropy)
3. Contextual divergence (informational perturbation)

We propose that *discernment* is precisely the state in which these entropies converge. When semantic essence remains stable under paraphrase, when autonomic regulation is coherent, and when contextual divergence is low, meaning becomes clear. When any domain destabilizes, discernment fails.

The present paper introduces:

- A formal definition of semantic essence
- A physiological entropy measure grounded in HRV
- A cross-domain Discernment Index (DI)
- Simulations showing how DI behaves under noise
- A human experiment for empirical validation

This approach aligns with mathematical psychology’s tradition of modeling cognition using quantitative, principled frameworks while incorporating contemporary insights from information theory, neuroscience, and computational semantics.

Theoretical Framework

Human discernment arises when linguistic and physiological systems jointly stabilize around a coherent interpretation. We formalize this claim across two domains—semantic and autonomic—each characterized by its own entropy landscape. Discernment is modeled as *entropy convergence*: the reduction of uncertainty across representations, contexts, and bodily states.

Semantic Essence

Meaning is rarely literal; it emerges as an attractor across variations. Paraphrases, contextual reformulations, and translation shifts all produce slightly different linguistic surfaces while preserving a deeper invariant—the *essence* of the message.

Let a stimulus S be re-expressed through n paraphrastic or contextual variants:

$$V = \{v_1, v_2, \dots, v_n\}$$

Using a modern embedding model $f(\cdot)$, each variant maps into a vector in semantic space:

$$E = \{f(v_1), f(v_2), \dots, f(v_n)\}$$

The covariance matrix of these embeddings is:

$$\Sigma = \text{Cov}(E)$$

Semantic entropy is defined as:

$$U_{\text{sem}} = \log \det (\Sigma + \varepsilon I) \quad (1)$$

where εI ensures numerical stability (Cover & Thomas, 2006).

Low U_{sem} indicates that paraphrastic variants converge toward a shared attractor—high semantic clarity.

High U_{sem} indicates dispersion—interpretive ambiguity.

We define semantic essence as the invariant vector minimizing entropy across perturbations:

$$A(S) = \arg \min_x \mathbb{E}[U_{\text{sem}}(S | \delta)] \quad (2)$$

where δ represents contextual noise, such as synonym substitution, varied pragmatic framing, or cross-linguistic translation.

This interpretation aligns with embedding research showing semantic stability under paraphrase clustering (Mikolov et al., 2013; Pennington et al., 2014; Devlin et al., 2019).

Figure 1 Semantic Essence Geometry.

A schematic representation of paraphrase embeddings clustering in low-entropy regions of semantic space, illustrating the attractor representing essence.

Autonomic Coherence

Cognition is embodied, and physiological regulation influences clarity. HRV is a validated measure of autonomic flexibility and coherence (Shaffer & Ginsberg, 2017). Low-frequency/high-amplitude variability corresponds to parasympathetic dominance, emotional regulation, and improved executive processing (Thayer & Lane, 2000).

We model autonomic dynamics as a stochastic time series:

$$P = \{p_1, p_2, \dots, p_m\}$$

representing instantaneous HRV-derived coherence scores.

Define the physiological entropy:

$$U_{\text{phys}} = - \sum_i p_i \log p_i \quad (3)$$

or equivalently, for continuous coherence estimates:

$$U_{\text{phys}} = \log(\sigma_{HRV} + \eta) \quad (4)$$

where σ_{HRV} is the variance of instantaneous vagal coherence and η prevents singularity.

High physiological entropy corresponds to autonomic instability—poor emotional grounding, heightened predictive error, and reduced clarity (Friston, 2010).

Low physiological entropy corresponds to coherent regulation, enabling stable interpretation.

Figure 2 Physiological Entropy Landscape.

Entropy values computed from HRV coherence distributions, demonstrating autonomic stability and instability states. depicts the physiological entropy landscape across HRV states.

2.3 Cross-Domain Entropy Convergence

Discernment emerges when semantic and physiological systems achieve coordinated low-entropy states.

Let:

- D = contextual divergence (e.g., KL-divergence between original and perturbed embeddings)
- U_{sem} = semantic entropy
- U_{phys} = physiological entropy

We define cross-domain entropy:

$$U_{\text{cross}} = \alpha D + \beta U_{\text{sem}} + \gamma U_{\text{phys}} \quad (5)$$

where α, β, γ weight the contributions of contextual, semantic, and physiological uncertainty.

Discernment is inversely related to cross-domain entropy:

$$DI = 1 - \frac{U_{\text{cross}}}{U^*} \quad (6)$$

where U^* is the maximum entropy observed under noise saturation.

A high DI reflects clear meaning extraction under low cognitive and autonomic uncertainty. A low DI reflects interpretive collapse under semantic noise, physiological dysregulation, or both.

Figure 3 Discernment Index Framework.

Cross-domain entropy model integrating semantic entropy, physiological entropy, and contextual divergence into a unified discernment measure.

Interpretation and Theoretical Implications

This model unifies:

- Information theory (entropy as uncertainty)
- Predictive processing (free-energy minimization)
- Semantic embeddings (vector clustering)
- Autonomic neuroscience (HRV coherence)

Discernment is redefined not as a metaphysical property but as a mathematically measurable state arising from convergent low-entropy dynamics. This contributes directly to mathematical psychology’s mission of formalizing cognitive processes with quantitative rigor.

Simulation Methods

To examine how the Discernment Index (DI) behaves under controlled perturbations, we conducted simulations of semantic and physiological noise interacting across the cross-domain entropy model. These simulations do not assume any specific embedding model or HRV sampling rate; instead, they illustrate general principles of entropy interaction.

Semantic Noise Simulation

Semantic noise was modeled by generating paraphrastic embedding clouds around a central “true essence” vector. For each trial:

1. A ground-truth vector $A(S)$ was generated in d -dimensional space.
2. Gaussian perturbations $\delta \sim \mathcal{N}(0, \sigma^2 I)$ were added to produce paraphrase embeddings.
3. Semantic entropy U_{sem} was computed via Equation (1).

As σ increased, embedding dispersion increased, producing predictable growth in semantic entropy. This aligns with theoretical expectations from information geometry and embedding theory (Cover & Thomas, 2006; Mikolov et al., 2013).

3.2 Physiological Noise Simulation

Autonomic states were simulated as coherence time series drawn from distributions representing:

- High coherence (low entropy)
- Moderate coherence
- Low coherence (high entropy due to dysregulation)

Each time series was used to compute U_{phys} via Equation (4).

Higher autonomic volatility led to elevated physiological entropy, consistent with empirical HRV research (Shaffer & Ginsberg, 2017).

3.3 Contextual Divergence

Contextual divergence D was modeled as KL-divergence between:

- Original semantic distribution
- Perturbed distribution under contextual shifts (topic framing, pragmatic adjustment, lexical substitution)

Larger divergences reflect greater interpretive strain.

3.4 Combined DI Distribution

For each simulation run:

$$DI = 1 - \frac{\alpha D + \beta U_{\text{sem}} + \gamma U_{\text{phys}}}{U^*}$$

Parameters were set so that $DI \in [0,1]$.

Representative behaviors:

- When semantic clarity was high and physiology stable \rightarrow DI approached 1.0.
- When embeddings dispersed or physiology destabilized \rightarrow DI collapsed toward 0.
- When both domains deteriorated \rightarrow DI exhibited superlinear decay, consistent with interacting noise effects in high-dimensional systems.

Figure 4 DI Simulation Results.

Representative Discernment Index behavior under increasing semantic noise, physiological noise, or combined perturbations.

These simulations demonstrate that discernment is not merely linguistic clarity nor bodily coherence—it emerges from their coupled stability.

4. Empirical Validation: Human Experiment

To empirically test the model, we propose a laboratory experiment integrating semantic stability judgments with HRV-derived autonomic measures.

4.1 Participants

A sample of 60 adults (18–65) with normal or corrected vision will participate. Sample size is based on prior HRV-cognition studies demonstrating medium effect sizes.

4.2 Stimuli

Stimuli consist of short statements (e.g., moral judgments, causal claims, emotionally charged sentences), each paired with:

- 6–10 paraphrases
- Contextual shifts (e.g., framing, modality changes)
- Controlled ambiguity conditions

Paraphrase embeddings will be precomputed to estimate ground-truth semantic entropy.

4.3 Procedure

1. Participants wear a validated HRV sensor (Polar H10 or equivalent).
2. They read a target statement and its paraphrases.
3. For each set, they judge:
 - “Do these sentences mean the same thing?”
 - “How confident are you?” (Likert scale)
4. HRV is recorded continuously.

Trial-level data will integrate:

- U_{sem} from embedding dispersion
- U_{phys} from HRV entropy
- D from contextual divergence

- Behavioral clarity ratings
 - Reaction times
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4.4 Predictions

The model yields several testable predictions:

Prediction 1 — DI predicts clarity.

Higher DI → higher confidence, lower RTs, greater consistency.

Prediction 2 — Semantic entropy moderates perceptual stability.

High U_{sem} → confusion, disagreement, and slower responses.

Prediction 3 — Physiological entropy constrains discernment.

High U_{phys} → lower DI, regardless of semantic clarity.

Prediction 4 — Cross-domain interaction dominates.

When *both* entropies are elevated, discernment collapses disproportionately.

This aligns with predictive coding frameworks (Friston, 2010; Clark, 2013) and HRV–executive function research (Thayer & Lane, 2000).

General Discussion

The cross-domain entropy model operationalizes discernment as an emergent property of convergent stability across semantic and physiological systems. Unlike purely linguistic or cognitive theories, this framework incorporates the entire organism—embodied uncertainty, contextual divergence, and semantic invariance.

Key contributions:

- First formal definition of semantic essence
- First integration of HRV entropy into a cognitive clarity model
- Introduction of the Discernment Index (DI)
- A mathematical foundation for future empirical research
- Compatibility with computational models (LLMs, embeddings)
- Relevance to clinical psychology, decision-making, and metacognition

This theoretical synthesis fits squarely within mathematical psychology’s mission to ground cognition in quantitative principles.

6. Limitations

Although the Discernment Index (DI) offers a unified quantitative framework, several limitations warrant acknowledgment.

6.1 Dependence on Embedding Models

Semantic entropy estimates depend on the embedding model used (e.g., GloVe vs. BERT). While essence emerges across paraphrases regardless of model architecture, absolute entropy values may vary. Future research should examine model-agnostic transformations or Bayesian corrections.

6.2 HRV as a Proxy for Autonomic Coherence

HRV provides a reliable but indirect measure of autonomic regulation. Factors such as respiration rate, physical conditioning, and medication can influence HRV metrics. Incorporating multi-modal physiological signals (e.g., EEG, skin conductance) may strengthen the physiological entropy construct.

6.3 Contextual Divergence Assumptions

KL-divergence is only one approach for modeling contextual mismatch. Alternative formulations (e.g., Wasserstein distance, Fisher information metrics) may provide better geometric sensitivity.

6.4 Generalization Constraints

Discernment involves more than semantic and autonomic stability—social cognition, emotional valence, and memory structure also shape clarity. The present framework focuses on the components most amenable to quantitative modeling, but does not attempt to exhaust the phenomenon.

Future Directions

The cross-domain entropy model opens multiple avenues for advancement:

7.1 Clinical Applications

DI could quantify cognitive instability in anxiety, trauma, or inflammatory disorders where autonomic dysregulation blunts clarity.

7.2 Artificial Intelligence Interfaces

Embedding-based essence extraction may serve as a stability constraint in LLM reasoning, reducing hallucination through entropy minimization.

7.3 Adaptive Human-Computer Systems

Real-time DI computation could support cognitive-load-aware interfaces, improving attention, learning, and decision-making.

7.4 Theoretical Extensions

Future models could integrate:

- Multimodal sensory entropy
- Bayesian predictive coding layers
- Reinforcement learning under physiological modulation

Discernment may ultimately be understood as a special case of organism-level free-energy minimization.

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