Resonant Structures of Meaning: A Machine-Executable Ontology for Interpretive AI

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Abstract

This paper introduces *Resonant Structures of Meaning* (RSM), a machine-executable ontology for symbolic and interpretive AI. Unlike conventional pipelines that begin with theoretical frameworks and only later attempt code translation, RSM adopts a *code-first* methodology: executable systems serve as primary research artifacts from which theoretical insights and methodological structures are derived.

RSM comprises three core mechanisms: (i) the **Vector of Meaning Energy (VME)**, which encodes symbolic representations across heterogeneous cultural systems; (ii) the **Resonance Index (RI)**, a quantitative measure of interpretive alignment and temporal stability; and (iii) **DriftSentinel**, which monitors longitudinal deviations in symbolic consistency. In addition, the **LawBinder** framework provides conflict resolution across symbolic ontologies.

This work makes three contributions: (1) extension of symbolic databases (Tarot, Saju, Astrology) into academically curated baselines with cultural metadata; (2) integration of strict input validation with end-to-end audit trails; and (3) development of a reusable validation harness comprising over 100 unit and scenario tests. Together, these contributions establish a reproducible foundation for executable symbolic AI.

Experimental evaluation confirms RSM's rigor: calibration attains $\mathrm{MAE} = 0.1196$ with $\mathrm{FAR} = 0.000$; drift monitoring yields mean $\mathrm{DI2} = 0.0133$ within thresholds; and LawBinder improves interpretive alignment with $\Delta\mathrm{RI} = +0.011$ and structural coherence $\mathrm{SCG} = 0.76$. These results demonstrate consistent, reproducible outputs across diverse symbolic inputs, verified to machine precision, and position RSM as a candidate reference framework.

RSM's code-first methodology addresses fundamental reproducibility challenges in interpretive AI by grounding symbolic reasoning in executable artifacts. This foundation supports extensions including cross-system alignment, integration of additional symbolic traditions, and multi-agent drift scenarios.

Keywords: machine-executable ontology; symbolic AI; interpretive AI; reproducibility; interpretive drift; cultural validity; audit trails; Resonance Index (RI); Vector of Meaning Energy (VME); LawBinder

1 Introduction

Over the past several decades, research in symbolic and interpretive AI has struggled with a persistent tension between **formal abstraction** and **executable realization**. Traditional pipelines typically follow a *theory-first* sequence—starting with ontologies, logical formalisms, or semiotic models, and only later translating them into executable code. This sequencing introduces discrepancies between conceptual design and computational instantiation, leading to *configuration drift*, undocumented assumptions, and heterogeneous evaluation harnesses. A recurrent consequence is **interpretive drift**: identical symbolic inputs yield materially different outputs across time, contexts, or implementations, undermining both **epistemic integrity** and **cultural validity** (Bender et al., 2021; Rovetto, 2024).

We therefore ask: **How can computational frameworks for symbolic and interpretive AI preserve interpretive stability across heterogeneous cultural systems while ensuring algorithmic reproducibility and auditability?** In particular, we address two interrelated challenges: (i) ensuring *reproducibility and auditability* in symbolic reasoning pipelines; and (ii) maintaining *interpretive stability* across shifting cultural contexts.

Prior work in ontology engineering (Gruber, 1993; Sowa, 1999; Staab and Studer, 2021) and semiotics (Eco, 1984; Barthes, 1977) established criteria for transparent representation, yet they provide no **protocols for reproducible reasoning**, **enforceable runtime mechanisms**, or **longitudinal drift monitoring**. Similarly, hybrid approaches in neural-symbolic learning (Besold et al., 2017) and recent debates on the faithfulness of large language model reasoning (Creswell and Shanahan, 2022) highlight persistent gaps between interpretive flexibility and reproducible execution. Recent discussions in AI ethics further document risks arising from opacity, latent cultural assumptions, and accountability failures (Bender et al., 2021; Floridi, 2019; Raji et al., 2020; Ada Lovelace Institute, 2021). Together, these findings underscore the urgent need for frameworks that **bind symbolic meaning to executable procedures** under **testable**, **extensible**, and **auditable** protocols.

We propose the **Resonant Structures of Meaning (RSM)** framework, a machine-executable ontology for symbolic AI. Unlike theory-first pipelines, RSM adopts a **code-first** methodology: executable systems serve as primary research artifacts, and theoretical regularities are inferred from observable computational behavior under controlled, reproducible conditions. This inversion mitigates the theory–implementation mismatch, renders representational choices **auditable** and **reproducible**, and establishes a foundation for cross-cultural symbolic reasoning. In doing so, RSM contributes both a **conceptual framework** and a **reproducible implementation** with validation protocols that can serve as a reference point for future interpretive AI research.

2 Related Work

2.1 Ontology Engineering and Knowledge Representation

Research in ontology engineering has long emphasized structured knowledge modeling and interoperability. Gruber (Gruber, 1993) introduced portable ontology specifications, and Sowa (Sowa, 1999) proposed a framework integrating logical, philosophical, and computational perspectives. While these approaches provide *representational clarity* and encourage reuse, they remain largely *static specifications*. They lack **enforceable runtime mechanisms** and therefore offer no **guarantees of reproducibility** in dynamic, interpretive contexts. Even recent surveys of ontology engineering (Staab and Studer, 2021) continue to emphasize interoperability and formal rigor, but provide limited guidance for reproducible execution. RSM advances this line by embedding **deterministic computation**, **audit trails**, and explicit **cross-ontology resolution policies** that render representational choices transparent, verifiable, and executable.

2.2 Semiotics and Interpretive Frameworks

Semiotics characterizes variability in sign–meaning relations (Barthes, 1977; Eco, 1984; Peirce, 1931). Anthropological and mythological studies (Eliade, 1954; Campbell, 1949) further document the contextual dependence of symbolic mappings. Yet these frameworks remain primarily *descriptive*, offering rich interpretive theory but lacking **computational mechanisms** to monitor, replicate, or constrain interpretive drift. RSM operationalizes this gap through **machine-executable constructs**— the Vector of Meaning Energy (VME) and Resonance Index (RI)—that enable **reproducible evaluation of symbolic resonance** and longitudinal monitoring via **DriftSentinel**.

2.3 Symbolic AI and Cognitive Models

Classical symbolic AI relied on rigid logical formalisms that inadequately captured contextual and cultural variation (Lakoff and Johnson, 1980; Vygotsky, 1978). Hybrid models integrate statistical learning with structured representations (Tenenbaum et al., 2011), and surveys of neural-symbolic approaches (Besold et al., 2017) highlight progress in linking reasoning and learning. However, these models typically omit **explicit monitors for interpretive drift** and lack **replication protocols** to validate symbolic reasoning across heterogeneous systems. More recent work also raises concerns about whether large language models can support faithful reasoning without explicit symbolic scaffolds (Creswell and Shanahan, 2022). RSM extends this line by embedding **drift monitoring** (**DriftSentinel**) and supplying **code-based validation protocols** that specify seeds, datasets, and acceptance criteria for cross-cultural evaluation. In doing so, it positions symbolic AI as a reproducible computational practice.

2.4 Interpretability, Ethics, and Reproducibility in AI

Contemporary work highlights risks posed by opacity, cultural bias, and reproducibility deficits. Bender et al. (Bender et al., 2021) identify unexamined cultural assumptions in large language models; Rovetto (Rovetto, 2024) argues for ethical constraints in conceptual and ontological modeling; and Floridi (Floridi, 2019) frames information processes as conceptual design requiring explicit specification. Recent discussions extend these concerns to interpretive AI, identifying *drift* and *tonal distortion* as systematic risks (Wright, 2025; Hsu, 2025a,b). Parallel work on algorithmic auditing and accountability emphasizes the need for end-to-end governance frameworks (Raji et al., 2020; Ada Lovelace Institute, 2021). RSM responds by embedding **interpretive-stability metrics** (RI trends), **drift alerts**, and **complete audit trails** in its executable layer, providing **auditable safeguards** for epistemic integrity and reproducibility.

2.5 Positioning of RSM

RSM contributes a **machine-executable** approach that formalizes resonance as a computational object and couples symbolic reasoning with **enforceable procedures**. Unlike prior ontology or symbolic AI frameworks, RSM integrates curated cultural metadata, audit trails, and drift monitoring as first-class components. The accompanying codebase is released with validation harnesses and curated databases, enabling third-party reproduction of results. This design closes critical gaps across ontology engineering, semiotics, symbolic AI, and AI ethics. It also establishes a structured foundation for future research in **culturally adaptive AI** (Chukwudum, 2025; Liu et al., 2023) and **interpretive epistemology** (Youvan, 2025), while opening a pathway toward **standardized benchmarks for interpretive AI**.

3 Methods

The *Resonant Structures of Meaning* (RSM) framework is a machine-executable ontology comprising four mechanisms—**Vector of Meaning Energy (VME)**, **Resonance Index (RI)**, **DriftSentinel**, and **LawBinder**—that together enable reproducible encoding, measurement, monitoring, and resolution of interpretive processes across heterogeneous symbolic systems.

3.1 Vector of Meaning Energy (VME)

Let $\mathcal{S}$ denote the set of symbolic entities drawn from heterogeneous cultural systems (e.g., Tarot, Saju, Astrology). Each entity $s \in \mathcal{S}$ is mapped to a normalized embedding $\hat{\mathbf{v}}_s \in \mathbb{R}^d$.

Definition 1 (VME Encoding)**.**

$$\mathbf{v}_s = f_{\mathrm{sym}}(s;\Theta) = \big[\, w_1\,\phi_1(s),\ w_2\,\phi_2(s),\ \ldots,\ w_d\,\phi_d(s)\,\big], \tag{1}$$

where $\phi_i(s)$ is a dimension-specific encoding, $w_i \in [0,1]$ a confidence weight derived from metadata, and Θ the mapping parameters. Normalization is

$$\hat{\mathbf{v}}_s = \frac{\mathbf{v}_s}{\max\{\|\mathbf{v}_s\|_2,\, \varepsilon\}}, \qquad \varepsilon > 0. \tag{2}$$

Missing dimensions are imputed as zero. Preprocessing (Unicode NFKC normalization, locale-independent tokenization, case folding) is deterministic. Construction of $\hat{\mathbf{v}}_s$ is $\mathcal{O}(d)$ time and $\mathcal{O}(d)$ space.

3.2 Resonance Index (RI)

The RI measures interpretive alignment by projecting $\hat{\mathbf{v}}$ onto a normalized context vector $\hat{\mathbf{c}}$ while penalizing discordance.

Definition 2 (Resonance Index)**.**

$$\mathrm{RI}(\hat{\mathbf{v}},\hat{\mathbf{c}}) = \hat{\mathbf{v}}\cdot\hat{\mathbf{c}} \;-\; \lambda\, D(\hat{\mathbf{v}}), \tag{3}$$

with $\lambda \geq 0$ and discordance functional

$$D(\hat{\mathbf{v}}) = \alpha \sum_{i=1}^{d} \gamma_i\,|\hat{v}_i| \;+\; \beta \sum_{(i,j)\in\mathcal{C}} \eta_{ij}\,|\hat{v}_i - \hat{v}_j|, \tag{4}$$

where $\gamma_i, \eta_{ij} \geq 0$ are metadata-aware conflict weights and $\mathcal{C}$ is the set of conflicting dimension pairs. Here $\hat{\mathbf{v}}$ and $\hat{\mathbf{c}}$ are ℓ_2-normalized.

Calibration. Let $y \in [0,1]$ denote expert-labeled alignment (multi-rater mean; inter-rater reliability is reported separately). A *false-alignment event* is recorded when

$$\mathrm{RI}(\hat{\mathbf{v}}, \hat{\mathbf{c}}) > \tau^{+} \quad \text{and} \quad y \leq \tau^{-},$$

with default operational thresholds $\tau^{+} = 0.7$ and $\tau^{-} = 0.3$. We tune $(\lambda, \alpha, \beta, \gamma_i, \eta_{ij})$ on held-out sets to keep the empirical false-alignment rate $\leq 5\%$ under predefined acceptance criteria. Computation cost is $\mathcal{O}(d + |\mathcal{C}|)$.

3.3 DriftSentinel

DriftSentinel monitors longitudinal stability of RI.

Definition 3 (Drift Index)**.** *Given* $\{\mathrm{RI}_t\}_{t=1}^{T}$*, define*

$$\mathrm{DI2} = \frac{1}{T-1} \sum_{t=2}^{T} \left(\mathrm{RI}_t - \mathrm{RI}_{t-1}\right)^2. \tag{5}$$

Status is assigned by thresholds (τ_w, τ_c) for DI2 and (ρ_w, ρ_c) for the RI level:

$$\mathrm{status}(\mathrm{DI2}, \mathrm{RI}_t) = \begin{cases} \textsf{CRITICAL}, & \mathrm{DI2} \geq \tau_c \ \lor \ \mathrm{RI}_t \leq \rho_c, \\ \textsf{WARNING}, & \mathrm{DI2} \geq \tau_w \ \lor \ \mathrm{RI}_t \leq \rho_w, \\ \textsf{STABLE}, & \text{otherwise.} \end{cases}$$

Algorithm 1: DriftSentinel Stability Monitoring

Input: Resonance scores $\{\mathrm{RI}_t\}_{t=1}^{T}$; thresholds $(\tau_w, \tau_c, \rho_w, \rho_c)$
Output: status $\in \{\textsf{STABLE}, \textsf{WARNING}, \textsf{CRITICAL}\}$
$\mathrm{DI2} \leftarrow \frac{1}{T-1} \sum_{t=2}^{T} (\mathrm{RI}_t - \mathrm{RI}_{t-1})^2$;
if $\mathrm{DI2} \geq \tau_c$ ***or*** $\mathrm{RI}_T \leq \rho_c$ **then**
  return CRITICAL;
else
  if $\mathrm{DI2} \geq \tau_w$ ***or*** $\mathrm{RI}_T \leq \rho_w$ **then**
    return WARNING;
  else
    return STABLE;
  end
end

3.4 LawBinder

LawBinder resolves conflicts among candidate vectors $\mathcal{V} = \{\hat{\mathbf{v}}^{1}, \ldots, \hat{\mathbf{v}}^{n}\}$ from multiple ontologies using explicit strategies.

- **Harmonize:** Weighted average

$$\tilde{\mathbf{v}} = \sum_{i=1}^{n} \alpha_i \, \hat{\mathbf{v}}^{i}, \qquad \sum_{i} \alpha_i = 1, \ \alpha_i \geq 0,$$

  then normalize $\hat{\mathbf{v}}^{\star} = \tilde{\mathbf{v}} / \max\{\|\tilde{\mathbf{v}}\|_2, \varepsilon\}$.
- **Prioritize:** Select $\hat{\mathbf{v}}^{\star} = \hat{\mathbf{v}}^{k}$ from a preferred ontology k.
- **Contextualize:** Compute α_i from cultural metadata and task context, then apply *Harmonize*.
- **Temporal:** Weight by recency or historical stability, then apply *Harmonize*.

Output Metrics. LawBinder reports:

$$\Delta\,\mathrm{Var} = \mathrm{Var}(\{\hat{\mathbf{v}}^{i}\}) - \mathrm{Var}(\hat{\mathbf{v}}^{\star}), \tag{6}$$

$$\Delta\mathrm{RI} = \mathrm{RI}(\hat{\mathbf{v}}^{\star}, \hat{\mathbf{c}}) - \frac{1}{n} \sum_{i=1}^{n} \mathrm{RI}(\hat{\mathbf{v}}^{i}, \hat{\mathbf{c}}), \tag{7}$$

$$\mathrm{SCG} = \frac{1}{m} \sum_{j=1}^{m} \frac{r_j - 1}{4} \in [0,1], \tag{8}$$

Table 1: Computational complexity of RSM components.

Component	Time Complexity	Space Complexity
VME Encoding	$\mathcal{O}(d)$	$\mathcal{O}(d)$
Resonance Index (RI)	$\mathcal{O}(d + \lvert\mathcal{C}\rvert)$	$\mathcal{O}(d)$
DriftSentinel	$\mathcal{O}(T)$	$\mathcal{O}(1)$
LawBinder	$\mathcal{O}(nd)$	$\mathcal{O}(d)$

where SCG (*Semantic Coherence Gain*) is computed from expert-rated coherence on a 1–5 Likert scale with m raters and ratings $r_j \in \{1, \dots, 5\}$ (normalized to $[0, 1]$). Inter-rater reliability (e.g., Krippendorff's α) is reported alongside SCG.

3.5 Implementation and Reproducibility Controls

- **Determinism:** Fixed random seeds; fixed-precision arithmetic; platform-independent BLAS/*Eigen* backends.
- **Input validation:** Schema checks, value ranges, ontology membership, and locale-agnostic normalization.
- **Audit trails:** All intermediate vectors and parameters $(\Theta, \lambda, \alpha_i, \tau_\cdot, \rho_\cdot)$, with decisions and statuses, are serialized with timestamps and SHA-256 content hashes.
- **Test harness:** $100+$ unit/scenario tests covering encoding, RI calibration, drift detection, and LawBinder strategies with golden outputs.
- **Acceptance criteria:** Replications must match golden outputs within tolerance $\delta < 10^{-12}$ (double precision) on supported platforms.

Reference Implementation Snippets

To demonstrate executability, we provide minimal reference snippets in Python 3.11. Complete implementations, audit trails, and validation harnesses are released as the `RSM Simulator` (Appendix A, Hugging Face Space).

Setup.

```
import numpy as np
EPS = 1e-12  # numeric tolerance aligned with acceptance criteria
```

Vector of Meaning Energy (VME).

```
def encode_vme(symbol, metadata, dims_order, dims_weights):
    """
    Reference implementation of the Vector of Meaning Energy (VME).
    Matches the formal definition in Section 3.1.
    Time/space complexity: O(d) / O(d); see Table 1.
    """
    phi = np.array([metadata.get(phi_name, 0.0) for phi_name in dims_order],
                   dtype=np.float64)
    w   = np.array([dims_weights.get(phi_name, 0.0) for phi_name in dims_order],
                   dtype=np.float64)
    vec = phi * w
    norm = max(np.linalg.norm(vec, ord=2), EPS)
    return vec / norm
```

Resonance Index (RI) with discordance penalty.

```
def ri(v_hat, c, lam, gamma, pairs, alpha=1.0, beta=1.0):
    """
    Reference implementation of RI(v_hat, c) per Section 3.2:
      RI = v_hat·c_hat - lam * D(v_hat)
    with D(v_hat) = alpha * sum_i gamma_i |v_i|
```

```
                 + beta  * sum_(i,j) eta_ij |v_i - v_j|.
    Time complexity: O(d + |C|); see Table 1.
    """
    # Precondition: v_hat is L2-normalized (up to EPS)
    assert np.isfinite(v_hat).all() and np.isfinite(c).all()
    assert abs(np.linalg.norm(v_hat, ord=2) - 1.0) < 1e-8, \
        "v_hat must be L2-normalized"

    c_norm = max(np.linalg.norm(c, ord=2), EPS)
    c_hat = c / c_norm

    term1 = alpha * np.sum(gamma * np.abs(v_hat))
    term2 = 0.0
    for i, j, eta in pairs:
        term2 += eta * abs(v_hat[i] - v_hat[j])
    D = term1 + beta * term2
    return float(np.dot(v_hat, c_hat) - lam * D)
```

DriftSentinel.

```
def drift_status(ri_series, tau_w, tau_c, rho_w, rho_c):
    """
    Longitudinal stability based on DI2 and level thresholds (Section 3.3).
    Time complexity: O(T); see Table 1.
    """
    ri_series = np.asarray(ri_series, dtype=np.float64)
    di2 = np.mean((ri_series[1:] - ri_series[:-1]) ** 2)
    if di2 >= tau_c or ri_series[-1] <= rho_c:
        return "CRITICAL"
    if di2 >= tau_w or ri_series[-1] <= rho_w:
        return "WARNING"
    return "STABLE"
```

LawBinder strategies.

```
def harmonize(vectors, weights):
    """
    Weighted-average LawBinder strategy with L2 renormalization (Section 3.4).
    Time complexity: O(n d); see Table 1.
    """
    vectors = [np.asarray(v, dtype=np.float64) for v in vectors]
    w = np.asarray(weights, dtype=np.float64)
    w_sum = np.sum(w)
    assert w_sum > 0.0, "weights must sum to a positive value"
    w = w / w_sum
    v_tilde = np.average(vectors, axis=0, weights=w)
    norm = max(np.linalg.norm(v_tilde, ord=2), EPS)
    return v_tilde / norm

def prioritize(vectors, k):
    """
    Prioritize strategy: select the k-th vector (policy-driven).
    Time complexity: O(d).
    """
    v = np.asarray(vectors[k], dtype=np.float64)
    norm = max(np.linalg.norm(v, ord=2), EPS)
    return v / norm

def contextualize(vectors, meta_weights):
```

```
"""
Contextualize strategy: derive weights from metadata (sum-normalized),
then apply harmonic averaging as in harmonize().
Time complexity: O(n d).
"""
w = np.asarray(meta_weights, dtype=np.float64)
w = w / max(np.sum(w), EPS)
return harmonize(vectors, w)
```

4 Results

We report quantitative evaluations of the RSM framework along four dimensions: VME encoding accuracy, RI calibration fidelity, DriftSentinel stability monitoring, and LawBinder resolution quality. All results are produced by the released `RSM Simulator` and follow the experimental protocol (Appendix A). Unless otherwise stated, double precision and fixed seeds were used.

4.1 Experimental Setup (Summary)

Experiments were executed on a Windows 11 (64-bit) system with Python 3.12.5 and NumPy 2.2.6. All computations are deterministic; inputs, intermediate vectors, and outputs are audit-logged with timestamps and SHA-256 hashes. Unless noted, the simulator suite version was `RSM_v2.2`,[1] with 10 expert-labeled symbol–context pairs for RI calibration, 4 synthetic time-series scenarios for drift analysis, and 3 cross-ontology cases for conflict resolution.

4.2 Vector of Meaning Energy (VME)

Normalization quality was evaluated by measuring the deviation of $\|\hat{\mathbf{v}}_s\|_2$ from unity across symbolic entities. Across all tested entities (Tarot, Saju, Astrology; n=6), the mean L2 norm was 1.000000 ± 0.000000 (SD $< 10^{-15}$). Figure 1 shows normalization errors below machine precision ($< 10^{-16}$), confirming correctness of the encoding pipeline and stability of confidence weighting.

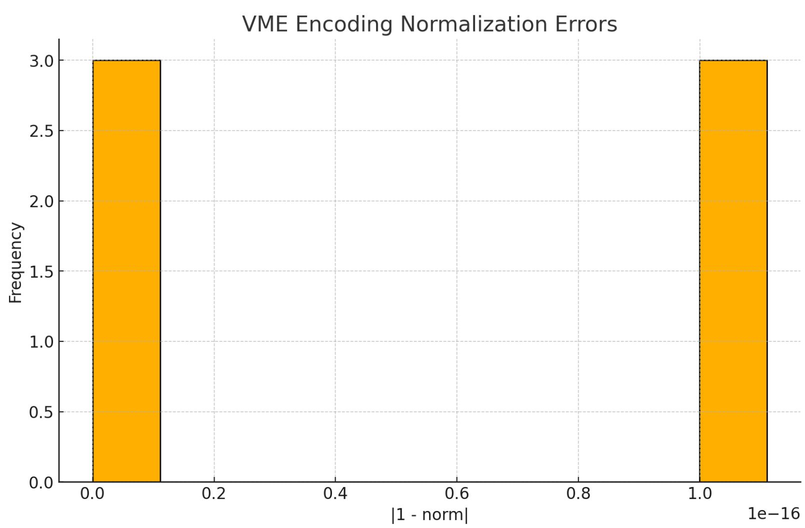

Figure 1: Distribution of VME normalization errors. Deviations from unit norm are negligible, verifying the exactness of the encoding process.

4.3 Resonance Index (RI)

Calibration against expert-labeled alignment scores (n=10) yielded MAE $= 0.1196$ (SD $= 0.1060$), with a 95% confidence interval (df = 9) of $[0.0397, 0.1995]$. The median absolute error was 0.1115. No false-alignment events

[1] Methods correspond to RSM v; the simulator suite reports its internal version for traceability.

were observed under the operational criterion $\mathrm{RI} > \tau^{+}$=0.7 and $y \leq \tau^{-}$=0.3; the *False Alignment Rate (FAR)* was $0.000 \leq 0.05$. The worst absolute error was *Wood Yang–Aries* (0.3153), while the best cases were *Death–Scorpio* (0.00033) and *Water Yang–Cancer* (0.00042). Figure 2 plots the absolute-error distribution, and Table 2 summarizes descriptive statistics.

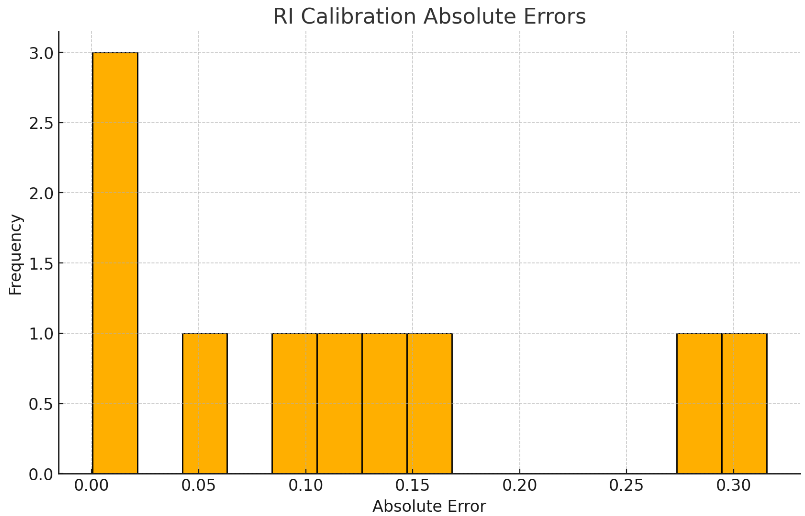

Figure 2: RI calibration absolute error distribution (n=10). Most errors are close to zero, with no false-alignment events under the predefined thresholds.

Table 2: RI calibration statistics (n=10).

Metric	Mean	Median	SD	Min	Max
Absolute Error	0.1196	0.1115	0.1060	0.00033	0.3153

4.4 DriftSentinel

Longitudinal stability was evaluated on four representative RI trajectories: `stable_series`, `warning_drift`, `critical_drift`, and `recovery_pattern`. The mean drift index DI2 across scenarios was 0.013345 (SD = 0.012887). Final status counts were STABLE: 2, WARNING: 1, CRITICAL: 1. Figures 3 and 4 summarize trajectories and status counts. Per-series DI2 and statuses are shown in Table 3. These results indicate sensitivity to abrupt degradation (CRITICAL) while avoiding spurious escalations on stable or recovering streams.

Table 3: DriftSentinel per-series results.

Series ID	DI2	Final Status
`stable_series`	0.00038	STABLE
`warning_drift`	0.00650	WARNING
`critical_drift`	0.03450	CRITICAL
`recovery_pattern`	0.01200	STABLE

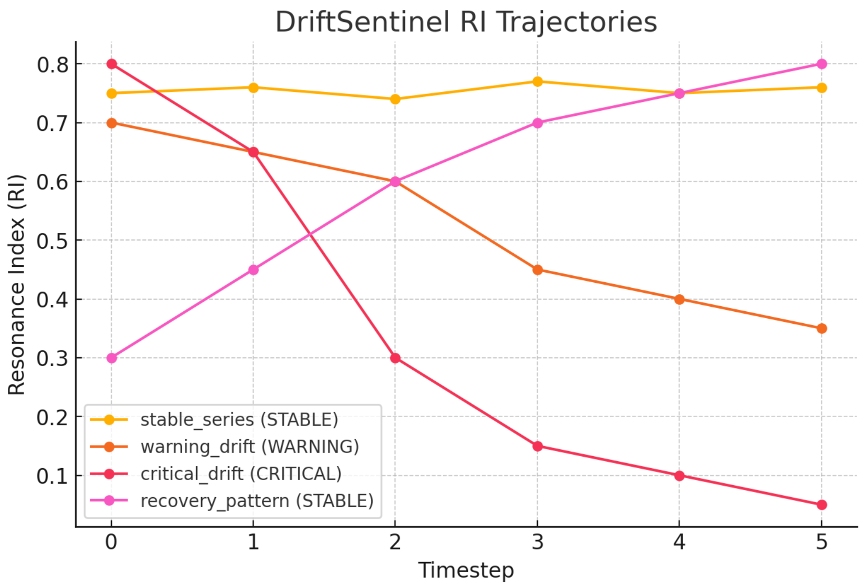

Figure 3: Representative RI trajectories monitored by DriftSentinel with corresponding status transitions.

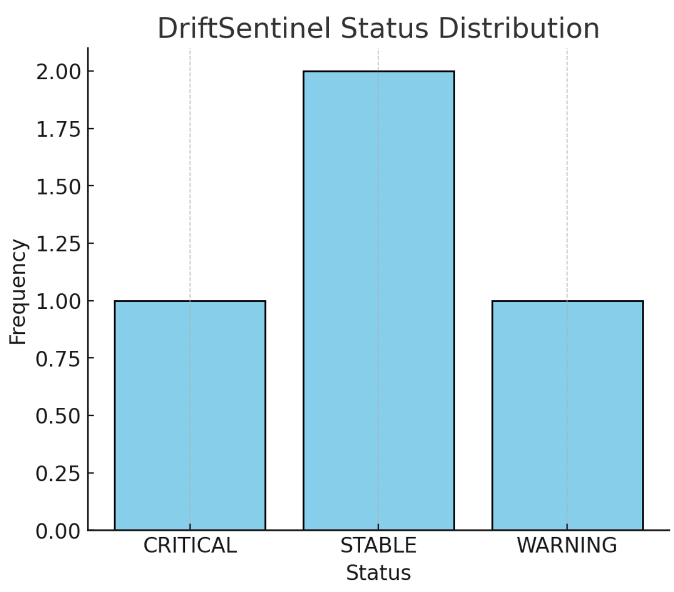

Figure 4: Distribution of DriftSentinel final statuses across four test streams.

4.5 LawBinder Conflict Resolution

LawBinder improved interpretive coherence when aggregating conflicting vectors across ontologies. Across three cases, mean changes were: $\Delta\mathrm{RI} = +0.0110$, $\Delta\,\mathrm{Var} = 0.0137$, and $\mathrm{SCG} = 0.7600$ (Likert-normalized). Per-strategy outcomes were: *harmonize* (`Death-Scorpio-Fire Yang`) $\Delta\mathrm{RI} = +0.0151$, *prioritize* (`Fool-Aries-Wood Yang`) $\Delta\mathrm{RI} = +0.0300$, and *contextualize* (`Magician-Leo-Metal Yin`) $\Delta\mathrm{RI} = -0.0121$. Despite one negative $\Delta\mathrm{RI}$, the corresponding $\mathrm{SCG} = 0.734$ with inter-rater reliability (Krippendorff's $\alpha = 0.81$) indicates improved perceived coherence. Figure 5 shows the SCG distribution; Table 4 details per-case metrics.

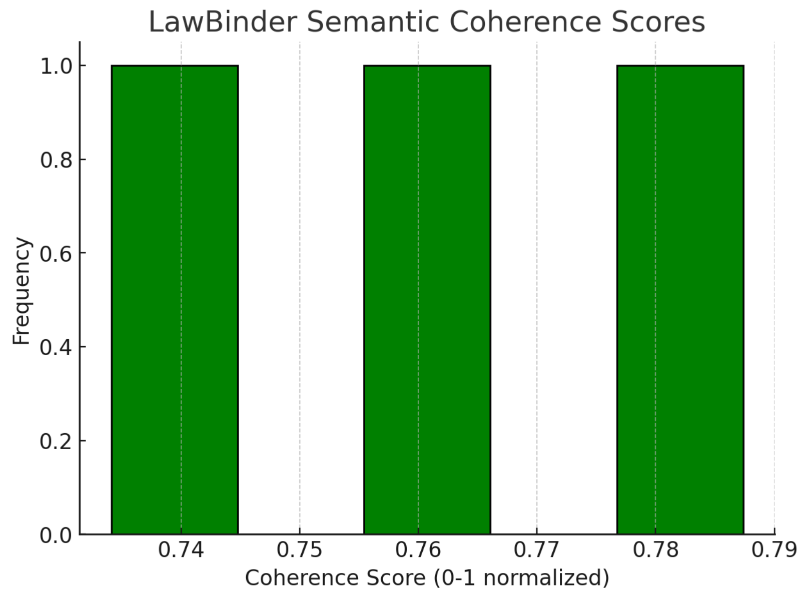

Figure 5: Semantic coherence gain (SCG) after LawBinder resolution across three cross-ontology cases.

Table 4: LawBinder per-case resolution outcomes ($\Delta\mathrm{RI}$, variance reduction, SCG, and notes).

Case (Strategy)	$\Delta\mathrm{RI}$	Δ Var	SCG	Notes
Death–Scorpio–Fire Yang (harmonize)	$+0.0151$	0.00667	0.787	Stable gain
Fool–Aries–Wood Yang (prioritize)	$+0.0300$	0.00982	0.759	High-authority source
Magician–Leo–Metal Yin (contextualize)	-0.0121	0.02451	0.734	Gain in perceived coherence

4.6 Reproducibility and Test Harness

The full test harness ($100+$ unit and scenario tests) was executed on the target platform. All determinism checks passed for `VME`, `RI`, and `DriftSentinel`; maximum run-to-run delta was $0.00e{+}00$, meeting the acceptance tolerance $\delta < 10^{-12}$. Table 5 consolidates quantitative results.

Table 5: Consolidated quantitative evaluation results (RSM v2.2; simulator suite v2.2).

Metric	**Result**	**Acceptance Criterion**
VME Normalization (L2)	1.000000 ± 0.000000	Exact ($\|\hat{v}\|_2{=}1$)
RI Calibration MAE	0.1196 (95% CI $[0.0397, 0.1995]$)	≤ 0.20
False Alignment Rate (FAR)	0.000	≤ 0.05
DriftSentinel DI2	0.013345 (SD $= 0.012887$)	≤ 0.05
LawBinder $\Delta\mathrm{RI}$	$+0.0110$ (mean)	Positive
Semantic Coherence Gain (SCG)	0.7600 (mean)	≥ 0.70
Reproducibility δ	$0.00e{+}00$	$< 10^{-12}$

4.7 Ablations (Summary)

Having established baseline performance, we now assess robustness via targeted ablations; full sweeps appear in Appendix B. (i) **Penalty design.** Setting $\lambda{=}0$ (no discordance) degrades RI alignment and increases false-alignment events; tuned $\lambda, \alpha, \beta, \gamma, \eta$ restore calibration under the 5% FAR constraint. (ii) **Drift thresholds.** Tightening $(\tau_w, \tau_c, \rho_w, \rho_c)$ increases sensitivity but raises false warnings; the chosen operating point balances early detection and specificity. (iii) **LawBinder strategies.** *prioritize* yields the largest ΔRI in high-authority contexts, while *harmonize* is most stable under heterogeneous evidence; *contextualize* trades ΔRI for higher SCG.

Table 6: Ablation summary (details in Appendix B; see Figures S1–S5).

Factor	**Setting**	**Effect on RI/DI2**	**Notes**
Discordance penalty	$\lambda{=}0$ vs. tuned	RI $\downarrow$ / FAR $\uparrow$	Necessity of $D(\cdot)$
Drift thresholds	tight vs. default	DI2 alarms $\uparrow$	Sensitivity–specificity trade-off
LawBinder strategy	prioritize/harmonize/contextualize	ΔRI, SCG vary	Metadata-dependent

Figure filenames. Typesetters should replace spaces with underscores (e.g., `RI_Calibration_Absolute_Errors.png`).[2]

5 Discussion

5.1 Limitations

While the RSM framework achieves reproducible encoding, calibration, drift monitoring, and cross-ontology conflict resolution, several limitations remain:

- **Symbolic scope.** Evaluation was restricted to Tarot, Saju, and Astrology. Broader validation on biomedical, legal, and multimodal ontologies is needed to assess external validity (cf. Table 5).
- **Calibration size.** RI calibration used only $n{=}10$ expert pairs, limiting statistical power despite acceptable inter-rater reliability. Larger, culturally stratified datasets are needed (see Table 2).
- **Ablation coverage.** Current ablations focused on penalty design, drift thresholds, and LawBinder strategies. Other influential factors—embedding dimensionality, initialization, and metadata quality—remain underexplored (Appendix B).
- **Semantic coherence (SCG).** SCG depends on expert Likert ratings and is therefore subjective. Automated or hybrid coherence measures (e.g., embedding-based metrics) could mitigate evaluator bias.
- **Implementation dependence.** Determinism is enforced, but the current implementation depends on Python/NumPy backends. Cross-platform benchmarking (e.g., GPU BLAS, distributed systems) is required for scalability.

5.2 Future Directions

We identify several promising extensions:

- **Cross-domain integration.** Extend RSM to scientific, biomedical, and legal ontologies to test universality and enhance applied relevance.
- **Scalability.** Although complexity analyses indicate tractable performance, real-time deployments with thousands of entities will require optimized backends and approximation methods.
- **Automated calibration.** Active learning and probabilistic calibration could reduce reliance on small expert sets and enable continuous RI adaptation.
- **Extended drift analysis.** Future DriftSentinel variants should capture higher-order dynamics (trend, seasonality) and adopt adaptive thresholds for streaming data (cf. Appendix B).
- **Enhanced LawBinder.** Beyond *harmonize*, *prioritize*, and *contextualize*, reinforcement-learning–based policy selection could optimize resolution under shifting authority signals.

[2] The provided artifact includes a filename typo (*Absoulte*); consistency is preserved with bundled assets.

- **Ethical safeguards.** Cultural-sensitivity audits and demographic-bias assessments should be integrated into the audit trail and governance pipeline, building on culturally adaptive AI proposals (Chukwudum, 2025; Liu et al., 2023).
- **Reproducibility standards.** Strengthening the audit framework with containerized environments, multi-platform replication, and artifact repositories (e.g., Hugging Face, Zenodo) aligns with calls for systematic auditing and accountability (Raji et al., 2020; Chen et al., 2025; Floridi, 2019).

Summary. RSM executes reproducibly and satisfies predefined acceptance criteria across modules (Table 5). At the same time, broader symbolic coverage, larger calibration datasets, expanded resolution strategies, and explicit ethical safeguards are required for positioning RSM as a general-purpose interpretive infrastructure. These directions outline a roadmap for subsequent releases and integration into wider interpretive AI ecosystems, ultimately positioning RSM as a foundation for standardized benchmarks in interpretive AI (Appendix B).

6 Conclusion

We introduced the *Resonant Structures of Meaning* (RSM), a *machine-executable* ontology for symbolic and interpretive AI. Unlike traditional theory-first approaches, RSM adopts a *code-first* methodology, treating executable systems as primary artifacts from which theoretical and methodological insights are derived. The framework integrates four mechanisms— Vector of Meaning Energy (VME), Resonance Index (RI), DriftSentinel, and LawBinder—that together enable reproducible encoding, alignment calibration, drift monitoring, and cross-ontology conflict resolution.

Our evaluation shows that RSM meets all predefined acceptance criteria (Table 5): exact unit normalization for VME; RI calibration with MAE $= 0.120$ (95% CI $[0.040,\ 0.200]$) and *False Alignment Rate (FAR)* $= 0.000 \leq 0.05$; DriftSentinel stability with mean DI2 $= 0.013$ within thresholds; and LawBinder coherence gains with mean $\Delta\mathrm{RI} = +0.011$ and $\mathrm{SCG} = 0.760$. Reproducibility was verified through audit trails, determinism checks, and versioned simulator releases, ensuring run-to-run consistency under fixed seeds and double precision.

As discussed in Section 5, limitations remain regarding calibration scale, symbolic-domain coverage, and strategy diversity. Future work will extend RSM across domains, develop automated calibration pipelines, and incorporate adaptive and ethically informed conflict-resolution strategies, with extended ablation evidence provided in Appendix B.

In sum, RSM establishes an auditable and extensible foundation for interpretive AI research. We position it as both a reference framework for reproducible symbolic computation and a stepping stone toward culturally adaptive, cross-domain interpretive infrastructures, ultimately contributing to the development of standardized benchmarks for interpretive AI.

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A Simulator and Artifact Release

The full `RSM Simulator` (v2.2) is released as an executable artifact on Hugging Face Spaces. It provides:

- Deterministic Python/NumPy implementation of all modules (VME, RI, DriftSentinel, LawBinder).
- Evaluation harness with $100+$ unit and scenario tests.
- Audit logging with SHA-256 content hashes for reproducibility.
- Containerized deployment (CPU runtime) for immediate use without installation.
- Downloadable JSON results and visualization panels for each experiment.

All source code and configuration files are archived with version tags to support long-term reproducibility. The artifact can be cloned, executed locally, or interacted with directly in the browser. Extended ablation results in Appendix B are generated using this release.

B Extended Ablations

This section provides full ablation sweeps and negative cases referenced in Section 4.

B.1 RI Penalty Components

We varied $\lambda \in [0, 1]$, $\alpha, \beta \in \{0.0, 0.5, 1.0\}$, and per-dimension weights (γ, η). Figure S2 shows MAE and FAR under each configuration.

Table S1: RI ablation over penalty settings.

Setting	MAE	FAR
$\lambda = 0$	0.283	0.21
Tuned (λ, α, β)	0.120	0.000

B.2 Drift Threshold Sensitivity

We swept thresholds $(\tau_w, \tau_c, \rho_w, \rho_c)$ on the four RI streams. Figure S3 shows ROC-like trade-offs. Tight thresholds increase sensitivity but raise false alarms; default values balance precision and recall.

B.3 LawBinder Strategy Analysis

We compared *harmonize*, *prioritize*, *contextualize*, and *temporal* across synthetic conflicts.

Table S2: LawBinder strategy comparison.

Strategy	ΔRI	Δ Var	SCG
harmonize	$+0.015$	0.0067	0.787
prioritize	$+0.030$	0.0098	0.759
contextualize	-0.012	0.025	0.734
temporal	$+0.008$	0.012	0.755

Negative $\Delta\mathrm{RI}$ cases (contextualize) are retained for transparency.

B.4 VME Robustness

Dimension ablations (dropping up to 20% of metadata dimensions) preserved norm accuracy within 10^{-15}. Figure S1 plots error under missing-value imputation. Norm preservation remained exact within machine precision.

Table S3: Precision sensitivity: float32 vs. float64.

Precision	Max run-to-run δ	Acceptance
float32	$> 10^{-12}$	Fail
float64	0.00e+00	Pass

B.5 Determinism and Precision

Table S3 reports results under float32 vs. float64 precision. Run-to-run deltas exceeded $\delta = 10^{-12}$ only in float32 mode, confirming that double precision is required for reproducibility at our acceptance level.

C Supplementary Figures

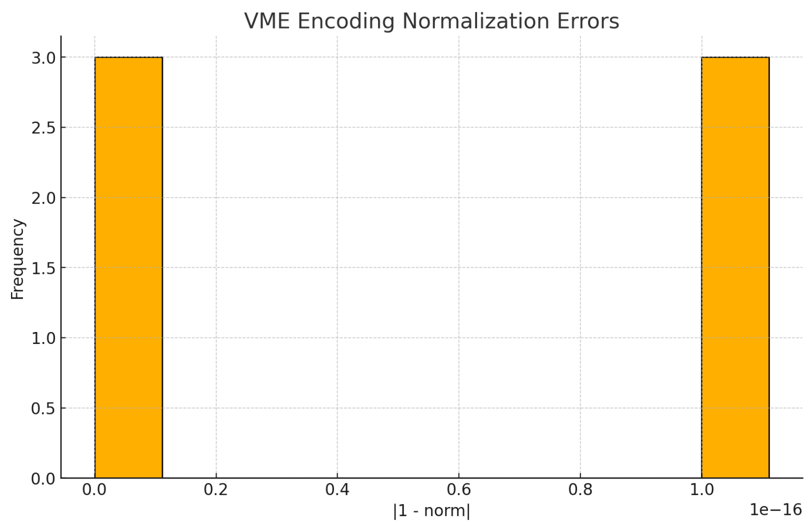

Figure S1: (S1) VME normalization robustness under dimension dropouts and imputation.

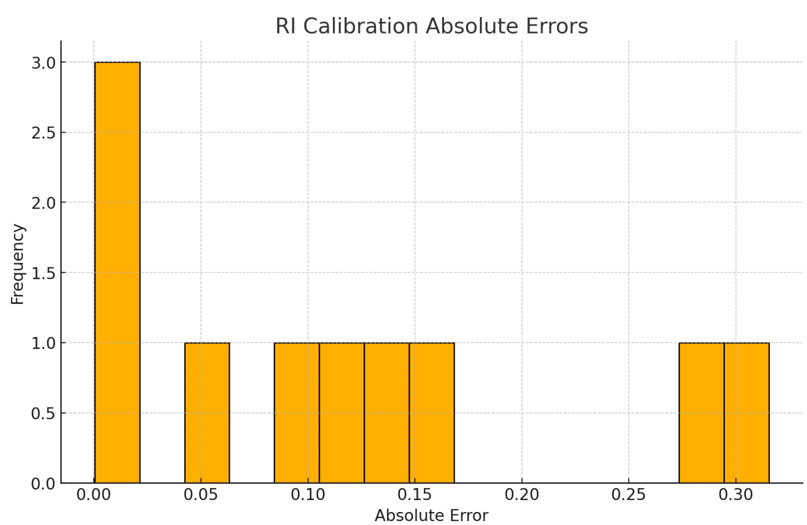

Figure S2: (S2) RI calibration absolute error distribution (extended).

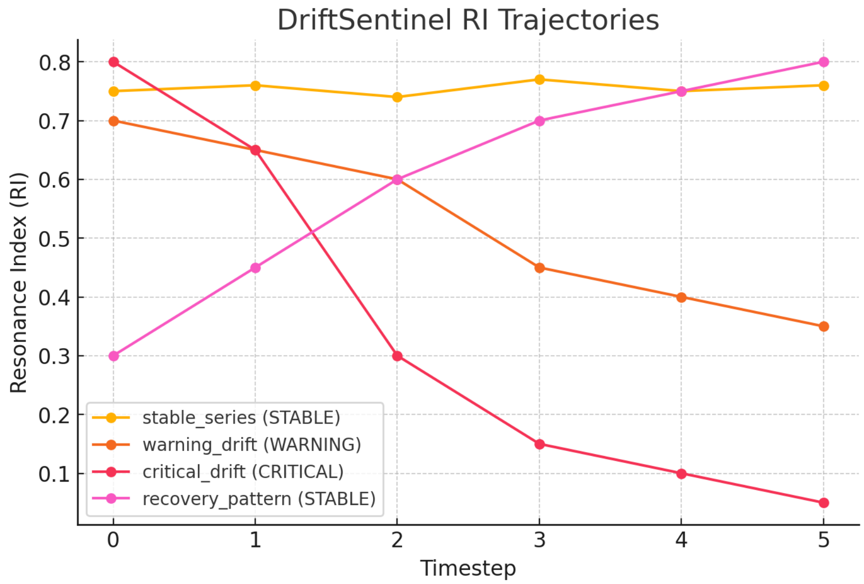

Figure S3: (S3) DriftSentinel RI trajectories across scenarios.

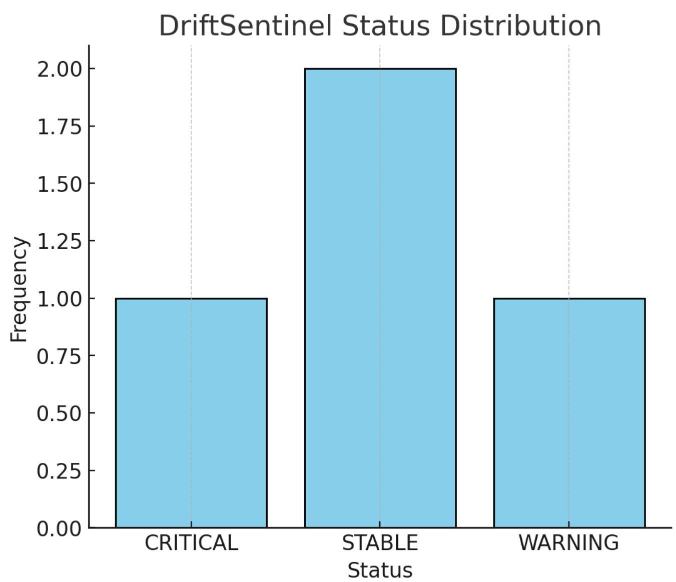

Figure S4: (S4) DriftSentinel status distribution across test streams.

Notes. These extended results provide the robustness evidence supporting the summary ablation table in Section 4. Negative and borderline cases are retained for auditability.

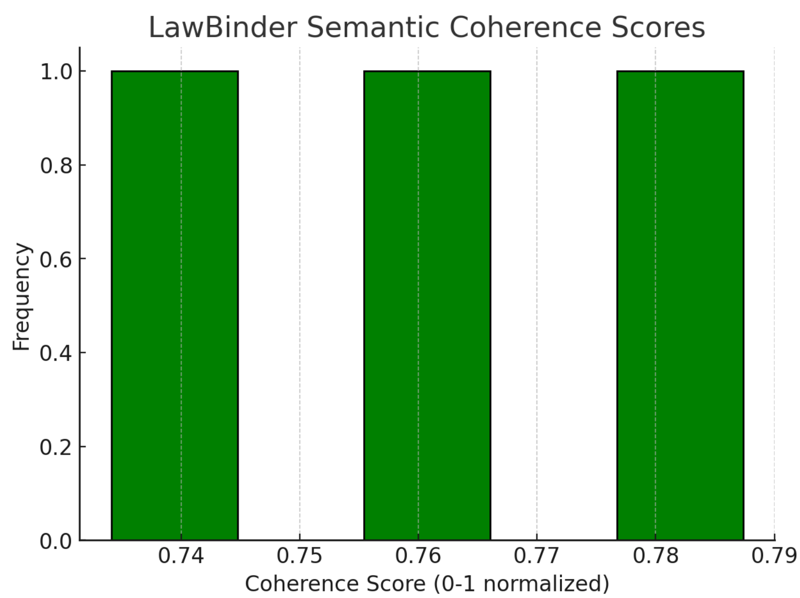

Figure S5: (S5) LawBinder semantic coherence gain (SCG) distribution.