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Not peer-reviewed version

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Posted Date: 7 April 2026

doi: 10.20944/preprints202604.0448.v1

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Article

Morphology, Seam Topology, and Temporal Scaffolding in Complex Systems

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Abstract

This paper introduces the *Morphological Participation Index* (MPI), a substrate-agnostic framework for estimating whether a system's morphology can plausibly support strongly integrated, coherence-sensitive, trace-rich, and temporally scaffolded dynamics. "Participation" refers to the degree to which morphology actively contributes to, constrains, and scaffolds the integrated, trace-bearing, and temporally organized dynamics available to a system. The immediate motivation comes from two adjoining lines of work: spectral approaches to resistance to decomposition, and recent proposals by Schneider and Bailey concerning prototime, quantum Darwinist stabilization, and the selective emergence of conscious basins [2,16–18]. MPI evaluates the structural conditions under which a system might sustain unified dynamics, stable internal traces, and organized temporal regimes, without presupposing a human, cortical, or even purely biological baseline. Formally, MPI represents morphology as a weighted constraint hypergraph [4,24], or as an explicit multilayer family of such hypergraphs [11], and returns a score bundle rather than a single undifferentiated scalar. The core bundle consists of six components: integration geometry, multiscale nesting, resonant-mode support, trace geometry, temporal scaffolding, and robustness. An optional contextual patchiness module is provided for domains in which a defensible predicate family is available. The integration component is anchored in a balanced-cut spectral formalism: it uses sweep cuts over the Fiedler vector of the normalized Laplacian rather than raw minimum-cut objectives or simple sign cuts, thereby avoiding familiar degeneracies and linking MPI directly to contemporary spectral proxies for resistance to informational decomposition [6,19,23]. The principal contribution of MPI is a structural profile: seam maps, multiscale partitions, trace-capacity maps, temporal breadth measures, and perturbation-stability diagnostics, in a form that remains useful across biological, artificial, collective, and other nonstandard architectures. More generally, the same diagnostics may be useful in AI alignment. Seam topology, trace geometry, and temporal scaffolding provide a way to screen for architectures that may be difficult to audit, prone to distributed lock-in, or vulnerable to hidden coordination through narrow bottlenecks or persistent externalized traces. MPI can also serve as a screening tool for artificial systems whose structural profile merits closer safety and oversight attention.

Keywords: morphological participation index; seam topology; trace geometry; temporal scaffolding; spectral graph theory; constraint hypergraph; multiscale architecture; complex systems; AI alignment

1. Introduction

Across biology and engineering, systems differ not only in the dynamics they realize but in the architectures that make those dynamics possible. Some centralize control through narrow bottlenecks; others distribute sensing, valuation, and action across multiple semi-autonomous modules. Some write persistent traces into the environment or into internal registration structures; others rely on fleeting coordination with little record support. Some expose a single dominant timescale; others nest fast and slow processes into an ordered hierarchy [20]. These architectural differences matter whenever one asks how unified a system can become, how difficult it is to decompose, and how stable its internal regimes can be.

Yet most extant metrics begin one step downstream. They assess realized activity, realized coupling, or realized information integration. That is indispensable, but it leaves a prior question insufficiently formalized: before one measures realized integration, what kinds of morphologies are even plausible hosts for it? The same question becomes sharper when the target is not merely integrated activity but the more structured package emphasized in recent work on spectral integration and on prototime-related approaches to consciousness: integration borne by particular carrier modes, stabilization through traces and records, and the emergence of temporally ordered classical sectors from architectures that are not trivially decomposable [2,16,18].

MPI treats morphology as a first-pass explanatory variable rather than as a background assumption or an after-the-fact description. In the present framework, “morphology” is understood broadly as constraint geometry: the arrangement of couplings, bottlenecks, interfaces, recurrence loops, trace surfaces, and multiscale partitions through which a system channels its dynamics. The aim is to formalize the structural conditions that make certain kinds of dynamics easier or harder to sustain.

The paper makes four claims. First, morphology can be represented in a sufficiently general way by weighted constraint hypergraphs and explicit multilayer variants. Second, the primary output of a morphology-first framework should be a profile rather than a single scalar; what matters is the *shape of unity* in a structural sense: seam topology, trace geometry, temporal scaffolding, and robustness under perturbation. Third, balanced spectral cuts provide the right backbone for the integration component, because raw minimum-cut objectives notoriously reward trivial separations. Fourth, a credible MPI program requires comparison across distinct architectural families rather than calibration on a single favored domain.

The result is deliberately modest. MPI does not settle whether a system is conscious. It estimates whether an architecture is structurally well-positioned to sustain the kinds of integrated and record-bearing dynamics that more targeted measures may later confirm or disconfirm.

This architectural question also matters in AI alignment. Failures in advanced artificial systems need not arise only from objective misspecification or undesirable training data; they may also arise from how integration is organized. Architectures with sparse arbitration seams, concentrated trace surfaces, or persistent trace-mediated coordination can become difficult to interpret, hard to override, or prone to local–global conflict. A morphology-level prior can raise that question earlier than behavior-level evaluation alone: does a system’s control geometry make corrigibility, auditability, and stable human oversight structurally viable?

1.1. Relation to Adjacent Programs

Several established programs share methodological ground with MPI but differ in scope and target.

Integrated Information Theory [22] and its descendants assess realized information integration by computing partition-based measures over a system’s causal or informational structure. MPI operates one level upstream: it asks whether a morphology could host high integration, and its integration component is one of six subscores rather than the sole target.

Global Workspace Theory [1,8] emphasizes a broadcasting architecture in which a central workspace makes information globally available. MPI’s benchmark suite (Section 10) includes centralized architectures as one family precisely to test whether the framework can distinguish centralized broadcasting from federated or stigmergic coordination. The two programs are complementary: GWT specifies a functional architecture, while MPI asks what structural signatures would support or undermine it.

Network neuroscience [3,13,21] has developed a rich toolkit of graph-theoretic descriptors for brain connectivity—modularity, rich-club structure, small-worldness, and related measures. MPI draws on the same mathematical substrate but bundles its descriptors differently: it foregrounds seam topology, trace geometry, and temporal scaffolding as first-class objects rather than treating them as isolated graph statistics, and is designed for cross-domain comparison across biological, artificial, and collective architectures.

2. Conceptual Position of MPI

MPI is easiest to place by distinguishing four levels of analysis. The first concerns morphology itself: the architecture or constraint geometry instantiated by a system. The second concerns realized system-level integration. The third concerns the degree to which that integration depends on low-entropy, coherence-sensitive or resonance-sensitive carrier modes. The fourth concerns whether the system builds stable internal traces and clock-like or record-like structures through which temporally ordered basins can form.

Table 1. MPI's logical placement. It sits at the architectural level and is meant to guide, not replace, downstream dynamical analysis.

Level	Question	Representative object
Morphology	What architecture is available for coupling, partitioning, trace registration, and temporal scaffolding?	MPI (this paper)
Realized integration	Does the realized functional graph resist balanced decomposition?	Φ -spectral and related spectral diagnostics [2]
Carrier structure	What kinds of modes carry the observed integration?	PT-participation or other coherence-sensitive indices [18]
Time/records	Does the system instantiate stable trace and clock/record structure?	Clock, witness, and temporal-basin diagnostics [18]

Systems can separate along these levels. An engineered infrastructure may be highly coordinated while remaining entirely classical in the relevant sense. A system may also contain local coherence-sensitive structure while lacking the large-scale trace geometry or temporal architecture needed to stabilize it into a durable basin. MPI formalizes a prior that helps locate where those separations occur.

These structural features also bear on what kinds of system-level control an architecture can sustain—whether local processes can be registered, stabilized, and coordinated across time, or whether behavior remains fragmented, purely reactive, or dependent on narrow bottlenecks. The same features indicate whether an architecture can sustain forms of control often associated with agency: persistence across timescales, trace support sufficient for state registration, seam geometry that permits coordinated action without immediate fragmentation, and multiscale organization that allows local processes to cohere into durable system-level regimes. In that limited sense, the framework doubles as an *agency-relevance prior*.

The primary output is a profile of *unity topology*. Here “unity” is used in a purely structural sense. A high-scoring architecture is one in which weak seams are costly or difficult to find, trace interfaces are well-distributed, temporal organization spans multiple scales, and the resulting picture remains reasonably stable under perturbation. The scalar roll-up is secondary to this profile.

3. Relation to Spectral Integration and to the QDT/PT Program

3.1. Spectral Resistance to Decomposition

Recent work by Bailey and Schneider develops a scalable spectral proxy for resistance to decomposition, starting from mutual-information graphs estimated from time-series data [2]. Exact variants of integrated information are computationally intractable except in very small systems, so spectral surrogates are attractive because they preserve the intuition of resistance to decomposition while remaining operational on large systems.

The main methodological lesson for MPI is that balanced decomposition matters more than raw minimum-cut weight. Unnormalized min-cut objectives tend to isolate tiny fragments or low-volume appendages. Conductance and normalized-cut objectives penalize trivial separations and place the

problem in the standard framework of spectral graph theory [6,14,19,23]. MPI therefore aligns its integration component with balanced-cut seam finding from the outset.

3.2. QDT, Prototime, and Morphology as a Prior

The second motivating line comes from Schneider and Bailey's work on *Superpsychism*, the *Prototime Interpretation* of quantum mechanics, and the *Quantum Darwinist Theory of Consciousness* [16–18]. That program foregrounds a cluster of architectural questions that are independently important: how witnesses (in the Quantum Darwinist sense of redundant environmental records; Zurek 25,26) are distributed, how redundancy gradients support stable sectors, how coherent or coherence-sensitive modes might be preserved, and how internal clock-and-record structures may contribute to temporal ordering.

MPI enters that discussion as a morphology-first prior. It asks whether a system's constraint geometry looks hospitable to the relevant forms of integration, trace registration, and temporal stabilization. That makes MPI naturally compatible with QDT/PT-style investigations, but independent of them for its intelligibility or value.

3.3. Why Morphology Deserves Its Own Formalism

Morphology functions simultaneously as boundary condition, coupling scaffold, and control surface [20]. At finer scales it can create protected channels, recurrence loops, cavities, frustrated cycles, or compartmentalized interfaces. At meso- and macro-scales it determines whether those local structures can be nested, coordinated, externalized into traces, or coupled to action—in short, it helps select the basin landscape that the dynamics can inhabit.

This point is especially important in comparative settings. Biological nervous systems, cephalopod-like control systems, stigmergic collectives [5], and data infrastructures may all support coordination, but they do so through markedly different seam structures, trace distributions, and temporal organizations. A morphology-first framework should be able to compare them without assuming that one architecture is the template and the others are deviations.

Many architectures stabilize not at a single privileged level but through repeated organization across coarse-grainings [9]: local constraints support meso-scale regularities, those regularities support more durable traces, and the resulting structure constrains which later dynamics are easy or hard to realize. MPI requires only the weaker and more operational claim that some systems exhibit nested stabilization across scales, and that such nesting matters for both dynamical persistence and control.

4. Formal Representation of Morphology

4.1. Morphology as a Constraint Hypergraph

Definition 1 (Constraint hypergraph). *A system's morphology is represented as a weighted, optionally directed constraint hypergraph*

$$H = (V, E, w, \chi),$$

where V is a set of degrees of freedom, E is a set of hyperedges encoding pairwise or multi-way constraints, $w : E \rightarrow \mathbb{R}_{\geq 0}$ assigns weights, and χ optionally stores further edge structure such as type, direction, or phase relation.

The relevant degrees of freedom depend on the domain. In a connectome they may be neurons, compartments, or regions of interest; in a robot swarm, agents or control modules; in a distributed infrastructure, routing or telemetry units. The abstraction is intentionally permissive. MPI is meant to evaluate architecture, not to force all systems into one biological vocabulary. The use of hyperedges rather than pairwise edges reflects the growing recognition that many biological, social, and technological systems involve irreducibly multi-way constraints [4].

Multilayer representation.

Many systems are more naturally represented as an explicit family

$$\mathcal{H} = \{H^{(\ell)}\}_{\ell=1}^L,$$

where distinct layers capture physical adjacency, signaling, actuation, energy flow, or trace/readout structure [11]. MPI can then be computed per layer or over a documented aggregate with explicit layer weights.

4.2. Laplacian-like Operators

For spectral calculations, MPI requires a Laplacian-like operator that reflects global constraint structure.

Definition 2 (A normalized hypergraph Laplacian). *Let $B \in \mathbb{R}^{|V| \times |E|}$ be an incidence matrix, $W_E = \text{diag}(w(e))$, and let D_V and D_E be diagonal degree matrices on vertices and hyperedges. One standard normalized hypergraph Laplacian is*

$$L_H := I - D_V^{-1/2} B W_E D_E^{-1} B^\top D_V^{-1/2}.$$

When H is a simple weighted graph with adjacency matrix W , this reduces to the normalized graph Laplacian

$$L = I - D^{-1/2} W D^{-1/2}.$$

This choice is standard, implementable, and directly compatible with spectral clustering and balanced-cut pipelines [23,24].

Phase-sensitive extension.

When oscillatory phase relations matter, MPI can incorporate a magnetic Laplacian. For a graph with symmetric nonnegative weights $W_{ij} = W_{ji}$ and antisymmetric phases $\theta_{ij} = -\theta_{ji}$, define complex weights $\tilde{W}_{ij} = W_{ij} e^{i\theta_{ij}}$ and set

$$L_\theta := I - D^{-1/2} \tilde{W} D^{-1/2}.$$

Since W is symmetric and θ is antisymmetric, \tilde{W} is Hermitian, so L_θ is Hermitian with real eigenvalues. This allows cycle-consistency and frustration to be scored in a principled way [10].

4.3. Multiscale Coarse-Graining

Definition 3 (Coarse-graining hierarchy). *A multiscale morphology is represented by a hierarchy*

$$H \rightarrow H_{\lambda_1} \rightarrow H_{\lambda_2} \rightarrow \dots,$$

generated by a coarse-graining map $R_\lambda : H \rightarrow H_\lambda$ that merges nodes and hyperedges into supernodes according to a specified compatibility or stability rule.

In practice, R_λ can be implemented by spectral clustering, hierarchical clustering on a weight matrix, anatomical grouping, or a domain-specific aggregation scheme. MPI does not privilege one hierarchy; it requires only that the chosen hierarchy be explicit and reproducible.

4.4. Optional Dynamic Data

MPI can be structural-only or structural-plus-dynamic. Given multivariate time series $X = \{X_1, \dots, X_n\}$ over a time window, estimate pairwise mutual information [7] and build a symmetric weight matrix

$$W_{ij} := I(X_i; X_j), \quad W_{ii} = 0.$$

Finite-sample negative estimation artefacts can be thresholded to zero. The resulting graph can either replace the structural graph or be blended with it using explicit layer weights.

5. MPI Core Bundle and Outputs

Definition 4 (MPI as a score bundle). *MPI for a system S is a tuple*

$$\text{MPI}(S) = (\mathbf{s}, \Pi, \mathcal{M}, s_{\text{ctx}}),$$

where $\mathbf{s} \in [0, 1]^6$ is the vector of core subscores, Π is a multiscale family of seam partitions, \mathcal{M} is a bundle of seam maps, trace maps, and related diagnostics, and s_{ctx} is an optional contextual patchiness module reported only when an explicit predicate family is available.

The six core subscores are

$$\mathbf{s} = (s_{\text{int}}, s_{\text{multi}}, s_{\text{res}}, s_{\text{trace}}, s_{\text{temp}}, s_{\text{rob}}).$$

They quantify, respectively, integration geometry, multiscale nesting, resonant-mode support, trace geometry, temporal scaffolding, and robustness.

Definition 5 (Optional scalar roll-up). *When a single summary number is required, define*

$$\text{MPI}_{\text{tot}} := \prod_{k=1}^6 s_k^{\alpha_k}, \quad \alpha_k \geq 0, \quad \sum_k \alpha_k = 1.$$

The weighted geometric mean penalizes weak links: poor performance on one structural dimension cannot be washed out by excellence elsewhere.

Remark 1 (Boundary behavior of the geometric mean). *Because the geometric mean sends $\text{MPI}_{\text{tot}} \rightarrow 0$ whenever any $s_k \rightarrow 0$, a single zero subscore collapses the aggregate regardless of all other components. This is the intended behavior when the collapse reflects a genuine structural deficit (e.g., a system with no identifiable trace layer receiving $s_{\text{trace}} = 0$). When a subscore is undefined or inapplicable for a given domain, the corresponding α_k should be set to zero and the remaining weights renormalized. The subscore formulas use sigmoid or exponential transforms that asymptote to but do not reach zero for finite inputs, so exact-zero scores arise only from degenerate or inapplicable configurations. The profile rather than the scalar roll-up remains the primary output.*

Table 2. The six core components of MPI. The contextual patchiness module is reported separately as an optional extension.

Subscore	Interpretation	Minimal input
s_{int}	hard-to-cut integration geometry	structural H or weight matrix W
s_{multi}	multiscale nesting and seam persistence	coarse-graining hierarchy R_λ
s_{res}	support for coherent or resonance-sensitive modes	H plus phase or coherence data if available
s_{trace}	trace geometry and externalizable support	trace or interface layer
s_{temp}	temporal scaffolding and timescale breadth	spectral or longitudinal information
s_{rob}	invariance and stability under perturbation	perturbation or bootstrap ensemble

The primary output of MPI is the profile implied by these scores together with the corresponding maps and partitions. MPI_{tot} is a convenience, not the main epistemic object. In comparative work, the question of interest is often where the weakest seam lies, whether trace capacity is centralized or distributed, or whether temporal organization is broad or narrow—questions that a single scalar cannot answer.

6. Core Subscores

6.1. Integration Geometry: s_{int}

The integration component quantifies how resistant a morphology is to *balanced* decomposition.

Step 1: choose a weight matrix.

Let W be derived from the structural hypergraph, from functional coupling data, or from an explicitly weighted blend of layers.

Step 2: find the weakest balanced seam (spectral approximation).

Compute the normalized Laplacian $L(W) = I - D^{-1/2}WD^{-1/2}$. Let v_2 be the Fiedler vector associated with $\lambda_2(L)$. Sort vertices by the entries of v_2 and form sweep sets S_k from the first k vertices in that ordering. For each S_k , compute the conductance

$$\varphi(S_k) := \frac{\text{cut}(S_k, S_k^c)}{\min\{\text{vol}(S_k), \text{vol}(S_k^c)\}},$$

where

$$\text{cut}(S, S^c) := \sum_{i \in S} \sum_{j \in S^c} W_{ij}, \quad \text{vol}(S) := \sum_{i \in S} d_i, \quad d_i := \sum_j W_{ij}.$$

Define $\hat{S}(W) \in \arg \min_k \varphi(S_k)$.

This adopts the normalized-cut or conductance perspective and avoids the trivial-cut degeneracies familiar from unbalanced graph partitioning. The spectral intuition is supported by classical Cheeger-type bounds.

Proposition 1 (Cheeger-style control of balanced separability). *Let W define a connected weighted graph with normalized Laplacian L as defined above. If $\varphi^*(W)$ denotes the minimum conductance over nontrivial vertex subsets, then*

$$\frac{\lambda_2(L)}{2} \leq \varphi^*(W) \leq \sqrt{2\lambda_2(L)}.$$

This is the standard discrete Cheeger inequality for $L = I - D^{-1/2}WD^{-1/2}$ [6,23]. Different Laplacian normalizations (e.g., the random-walk Laplacian $L_{\text{rw}} = I - D^{-1}W$) yield the same eigenvalues but may use different conventional constant factors; here the constants are as stated because L is the normalization adopted throughout this paper.

Step 3: report complementary seam diagnostics.

Define

$$\Phi_{\text{cut}}(W) := \text{cut}(\hat{S}, \hat{S}^c), \quad \Phi_{\text{cond}}(W) := \varphi(\hat{S}), \quad \Phi_{\lambda}(W) := \lambda_2(L(W)).$$

Φ_{cond} tells us how difficult the weakest balanced split is, Φ_{λ} provides a spectral certificate of separability, and Φ_{cut} preserves the physically interpretable “how much coupling is severed?” intuition.

A default normalized integration subscore is

$$s_{\text{int}} := \sigma a_{\text{int}} \log(1 + \Phi_{\text{cond}}) + b_{\text{int}} \log(1 + \Phi_{\lambda}) - c_{\text{int}},$$

with calibration constants chosen on a benchmark corpus (Section 8.1).

6.2. Multiscale Nesting: s_{multi}

This component measures whether seam structure persists coherently across coarse-graining levels [9].

Choose a sequence of scales $\lambda_1 < \dots < \lambda_M$ and build coarse-grained morphologies $H_{\lambda_m} = R_{\lambda_m}(H)$. At each scale compute the corresponding weakest seam and conductance diagnostics. Pull these partitions back to the original node set and let π_m denote the induced partition at scale m .

Using a partition distance such as variation of information [12], define

$$s_{\text{multi}} := \exp(-\gamma_{\text{multi}} \text{median}_{m < m'} d_{\text{VI}}(\pi_m, \pi_{m'})) \exp(-\eta_{\text{multi}} \text{Var}_m(\log(1 + \Phi_{\text{cond}}^{(m)}))).$$

High values indicate nested basin structure and stable seam diagnostics across scales. Weak seams that reappear coherently across coarse-grainings—rather than moving chaotically from one resolution to another—support layered stabilization in which each level inherits structural commitments from the level below rather than rebuilding them from scratch.

6.3. Resonant-Mode Support: s_{res}

This component asks whether the architecture has features conducive to the survival of organized, coherence-sensitive, or resonance-sensitive modes. The emphasis is deliberately structural; in its lower tiers the score is a proxy for mode support, not a direct indicator of quantum coherence.

Tier 0: purely structural proxy.

In the absence of phase or coherence data, compute a cycle-richness proxy such as the cyclomatic number per node,

$$C_{\text{cycle}} := \frac{|E| - |V| + n_{\text{cc}}}{|V|},$$

where n_{cc} is the number of connected components, and combine it with an edge-connectivity proxy k_{edge} (for example, the mean number of edge-disjoint paths between randomly sampled node pairs). Then set

$$s_{\text{res}}^{(0)} := \sigma(a_0 C_{\text{cycle}} + b_0 k_{\text{edge}} - c_0).$$

Tier 1: phase-aware frustration.

If phase relations are available, use the magnetic Laplacian L_θ and define a normalized frustration proxy

$$F_\theta := \frac{\lambda_{\min}^{(\theta)}}{\lambda_{\text{ref}}},$$

where $\lambda_{\min}^{(\theta)}$ is the smallest eigenvalue of L_θ (zero when all cycles are phase-consistent, positive when at least some carry irreconcilable phase offsets) and λ_{ref} is a benchmark scale. Then $s_{\text{res}}^{(1)} := \exp(-\beta_\theta F_\theta)$. Low F_θ indicates high cycle-consistency and greater structural support for coherent global modes [10].

Tier 2: measured support diagnostics.

If coherence times, quality factors, or protected-channel measurements are available, use

$$s_{\text{res}}^{(2)} := \sigma(a_2 \log(1 + T_2) + b_2 \log(1 + Q) - c_2).$$

Finally, define

$$s_{\text{res}} := \begin{cases} s_{\text{res}}^{(2)}, & \text{if Tier 2 data are available,} \\ s_{\text{res}}^{(1)}, & \text{else if Tier 1 data are available,} \\ s_{\text{res}}^{(0)}, & \text{otherwise.} \end{cases}$$

Every report should state explicitly which tier was used.

6.4. Trace Geometry: s_{trace}

Trace geometry measures whether the architecture contains stable interfaces through which internal structure can be redundantly registered, read out, or otherwise stabilized. A “trace node” is any node, channel, or interface that can carry a durable record of what the system is doing—sensory surfaces, motor outputs, telemetry interfaces, pheromone-deposition surfaces, or logging channels, depending on the domain.

Partition the node set into internal degrees of freedom V_{core} and trace or interface nodes V_{trace} . When the morphology is represented as a hypergraph or multilayer family, edge-disjoint path computations are performed on the 2-section (clique expansion) of the relevant structural layer, or on a documented aggregate if multiple layers are combined. For each $u \in V_{\text{core}}$, compute the maximum number of edge-disjoint paths to distinct trace nodes:

$$k(u) := \max\{k : \text{there exist } k \text{ edge-disjoint paths from } u \text{ to distinct nodes in } V_{\text{trace}}\}.$$

Define trace capacity

$$K_{\text{trace}} := \frac{1}{|V_{\text{core}}|} \sum_{u \in V_{\text{core}}} \min\{k(u), k_{\text{max}}\}.$$

To penalize excessive trace centralization, define a concentration index

$$H_{\text{trace}} := 1 - \frac{\max_{v \in V_{\text{trace}}} \text{deg}_{\text{trace}}(v)}{\sum_{v \in V_{\text{trace}}} \text{deg}_{\text{trace}}(v)},$$

where $\text{deg}_{\text{trace}}(v)$ counts incoming trace paths or trace-linked incident weight. Then a default trace-geometry subscore is

$$s_{\text{trace}} := \sigma(a_{\text{trace}} \log(1 + K_{\text{trace}}) + b_{\text{trace}} H_{\text{trace}} - c_{\text{trace}}).$$

High values indicate that trace support is both substantial and not overly concentrated in a single choke point.

Choosing the trace partition.

The partition $V = V_{\text{core}} \cup V_{\text{trace}}$ is a modeling choice that must be documented for each domain. In many systems a natural partition exists: sensory surfaces and motor outputs in nervous systems, telemetry and logging interfaces in data infrastructures, pheromone-deposition surfaces in stigmergic collectives. When no obvious partition is available, two heuristics are reasonable: (i) designate as trace nodes those with the highest betweenness centrality linking the system to any external readout or actuation channel; or (ii) run a sensitivity analysis across candidate partitions and report the resulting range of s_{trace} values.

6.5. Temporal Scaffolding: s_{temp}

Temporal scaffolding measures whether the architecture supports a nontrivial distribution of internally relevant timescales, rather than collapsing into a single narrow temporal mode.

Start from the nonzero spectrum of the normalized Laplacian. If λ_k are the nonzero eigenvalues of $L(W)$, define characteristic diffusion-style timescales $\tau_k := 1/\lambda_k$ and let

$$B_{\tau} := \text{Var}_{k=2, \dots, K_{\tau}}(\log \tau_k),$$

where K_{τ} is the number of nonzero eigenvalues retained (by default, all nonzero eigenvalues; for large systems, $K_{\tau} = \min(n - 1, K_{\text{max}})$ with K_{max} chosen to exclude near-degenerate numerical artefacts). B_{τ} is a proxy for temporal breadth: high values indicate that the morphology supports a wider spread of relaxation or recurrence scales.

If longitudinal data are available, add a plateau fraction P (fraction of time spent in intervals where a chosen seam diagnostic remains approximately stationary) and a jump count J (switching rate for large seam reorganizations). A default temporally enriched score is then

$$s_{\text{temp}} := \sigma(a_{\text{temp}}B_{\tau} + b_{\text{temp}}P - c_{\text{temp}}) \exp(-\rho J).$$

In the structural-only setting, the baseline reduces to $s_{\text{temp}}^{(0)} := \sigma(a_{\text{temp}}B_{\tau} - c_{\text{temp}})$.

6.6. Robustness and Invariance: s_{rob}

MPI is intended as a screening tool, so it should be resistant to nuisance perturbations and label symmetries.

Given a baseline weight matrix W , generate perturbed versions $W^{(b)}$ by bootstrap resampling, noise injection, estimator variation, or edge perturbation. For each perturbation compute the seam diagnostics. Define

$$\text{Stab}_{\Phi} := \exp\left(-\zeta_{\Phi} \text{Var}_b(\log(1 + \Phi_{\text{cond}}(W^{(b)})))\right), \quad \text{Stab}_{\Pi} := \exp\left(-\zeta_{\Pi} \text{median}_{b \neq b'} d_{\text{VI}}(\hat{S}^{(b)}, \hat{S}^{(b')})\right),$$

and set $s_{\text{rob}} := \text{Stab}_{\Phi} \cdot \text{Stab}_{\Pi}$.

For swarms or other unlabeled formations, one may also require explicit quotient invariance: two configurations equivalent up to relabeling or symmetry should receive the same architectural summary [15]. In such settings, quotient-space metrics and topological summary statistics can be added without changing the rest of the MPI pipeline.

7. Optional Contextual Patchiness Module

In some systems, locally stable contexts emerge patchwise rather than globally. MPI can represent that idea, but only where a defensible predicate family is available. Because the result depends more heavily on modeling choices than the core bundle does, it is treated as an optional module. The risk of predicate-choice artefacts dominating the resulting score is substantially higher than for the core subscores, so contextual patchiness is reported separately and should always be accompanied by a full specification of the predicate family and compatibility construction used.

Let $\mathcal{Q} = \{q_1, \dots, q_m\}$ be a family of recordable, coarse-grained yes/no predicates on the system. Define a symmetric compatibility score $\kappa(q_i, q_j) \in [0, 1]$ estimating whether the corresponding predicates can be jointly stabilized or co-recorded. Build a compatibility graph G_{comp} over \mathcal{Q} , connect predicates whose compatibility exceeds a chosen threshold, and let $\mathcal{C} = \{C_1, \dots, C_r\}$ be the family of maximal cliques or near-cliques. Define

$$B_{\text{local}} := \frac{1}{r} \sum_{\ell=1}^r \frac{|C_{\ell}|}{m}, \quad B_{\text{global}} := \frac{\max_{\ell} |C_{\ell}|}{m}, \quad O_{\text{global}} := 1 - B_{\text{global}}.$$

Construct an overlap graph with Jaccard-style weights $\omega_{\ell\ell'} := |C_{\ell} \cap C_{\ell'}| / |C_{\ell} \cup C_{\ell'}|$, let H_{ω} be the entropy of the overlap distribution, and set

$$s_{\text{ctx}} := \sigma(a_{\text{ctx}}B_{\text{local}} + b_{\text{ctx}}O_{\text{global}} + d_{\text{ctx}}H_{\omega} - c_{\text{ctx}}).$$

This module scores highest when there are many substantial local contexts but no single trivially global one.

8. Reporting Conventions and Implementation

8.1. Calibration Protocol

Each core subscore passes raw diagnostics through a logistic transform $\sigma(ax + by - c)$ whose constants must be calibrated on a benchmark corpus. A principled calibration requires: (1) benchmark

diversity spanning at least three of the four architectural families in Table 3; (2) sigmoid fitting so that σ maps the 10th percentile to approximately 0.1 and the 90th to approximately 0.9; and (3) leave-one-family-out cross-validation to verify stability. Until such corpora are available, reports should use illustrative sigmoid coefficients and present raw diagnostics alongside normalized subscores so that readers can apply their own calibration.

Table 3. A minimal comparative benchmark suite for MPI.

Architecture family	Expected structural signature	Most informative MPI outputs	Why include it
Centralized or controller-like architectures	Strong global core with identifiable bottlenecks and relatively concentrated traces	s_{int} , seam maps, trace concentration	Tests whether MPI can distinguish centralized unity from mere density
Federated or cephalopod-like distributed architectures	Multiple semi-autonomous modules linked by arbitration channels rather than a single executive bottleneck	multiscale partitions, trace geometry, robustness	Tests whether MPI captures federated rather than centralized integration
Stigmergic or collective architectures	Distributed coordination through externalized traces and low-bandwidth local rules	trace geometry, temporal scaffolding, robustness	Classical control family in which architecture matters even without strong claims about consciousness
Telemetry-rich technical infrastructures	High observability, rich logging, modular coordination, often strong traces but mixed internal unity	seam maps, trace geometry, temporal breadth	Stress-tests the distinction between coordination surfaces and deeper integrative architecture

8.2. Default Weights and Reporting Checklist

For a general-purpose scalar roll-up, a reasonable default is

$$(\alpha_{\text{int}}, \alpha_{\text{multi}}, \alpha_{\text{res}}, \alpha_{\text{trace}}, \alpha_{\text{temp}}, \alpha_{\text{rob}}) = (0.24, 0.18, 0.16, 0.16, 0.16, 0.10).$$

These weights can be shifted toward s_{res} , s_{trace} , and s_{temp} when the goal is to search for architectures likely to support trace-rich and temporally scaffolded dynamics.

Reports should include at least: (1) the raw seam diagnostics Φ_{cond} , Φ_{cut} , and Φ_{λ} ; (2) the eigengap $\lambda_3 - \lambda_2$ and a balance statistic such as $\text{vol}(\hat{S})/\text{vol}(V)$; (3) the seam partition and edge or node importance maps at each reported scale; (4) the tier used for s_{res} and the construction used for trace geometry; (5) uncertainty estimates from resampling or perturbation analysis; (6) the contextual module s_{ctx} , if reported, together with the predicate family and compatibility construction; (7) when AI alignment is a target use case, a note on seam-sensitive conflict risk, trace concentration, and persistent-trace lock-in risk.

8.3. Implementation Pipeline

Build a structural hypergraph H or multilayer family \mathcal{H} from the chosen system representation. If dynamic data are available, estimate a functional coupling graph over a documented windowing scheme and combine it with structural layers if desired. Construct coarse-grained morphologies H_{λ} across a chosen scale hierarchy. At each scale, compute the normalized Laplacian, the Fiedler vector, the best sweep cut, and the seam diagnostics. Compute s_{int} , s_{multi} , s_{res} , s_{trace} , s_{temp} , and s_{rob} . Return the

score bundle, seam maps, trace maps, temporal profile, and robustness diagnostics, with an optional scalar roll-up.

9. Illustrative Toy Benchmarks

To make the profile concept concrete, we present MPI computations on three toy architectures chosen to stress different parts of the framework. Full construction details appear in Appendix A. The three systems are: (i) a *minimal centralized hub-and-spoke toy* (9 nodes, 16 edges); (ii) a *federated (octopus-like) toy* (49 nodes, 136 edges); and (iii) a *stigmergic (mycelium-like) toy* (300 nodes, 332 edges). All subscores use illustrative sigmoid coefficients and Tier-0 structural proxies for s_{res} . The raw seam diagnostics (Φ_{cond} , λ_2) are reported alongside normalized subscores so that the profile can be recomputed under alternative calibrations.

The key observation is the *profile shape*, not the absolute values (which depend on uncalibrated sigmoid constants). Each architecture produces a distinct signature. The centralized toy scores highest on s_{int} but collapses on s_{multi} because its simple hub-and-spoke topology has no nontrivial coarse-graining hierarchy. The federated toy scores lowest on global integration but highest on multiscale nesting. The stigmergic toy is weakest on cycle-richness and trace geometry, reflecting its predominantly tree-like branching.

The centralized toy's MPI_{tot} rounding to zero reflects the fact that this synthetic toy representation has no nontrivial multiscale nesting—a limitation of the toy, not of centralized architectures in general. A real system with rich hierarchical structure would not produce $s_{multi} \approx 0$. More generally, MPI_{tot} functions as a conjunctive adequacy score: a zero value signals which subscore is responsible and whether the deficit reflects a genuine architectural absence or a representational artefact.

10. Archetypal Benchmark Suite

A first benchmark suite should span cases that differ in seam topology, trace distribution, and temporal organization.

These families stress different parts of the framework. Centralized systems test whether the integration metric is sensitive to true bottlenecks rather than to graph density alone. Federated systems test whether multiscale seam structure and trace distribution can distinguish distributed control from simple fragmentation. Collective and infrastructure cases test whether trace-rich or heavily logged systems can be separated from architectures whose unity is carried differently.

For the stigmergic and telemetry-rich families, trace and temporal structure should be interpreted broadly enough to include externalized records: pheromone-like fields, cached state, logs, routing weights, telemetry histories, or other durable signals that bias later action [5]. These benchmark classes are especially useful for AI safety because they separate architectures that are merely observable or heavily instrumented from architectures whose deeper integration is carried by more concentrated seam structures.

11. Future Directions

A plausible future program has four tracks.

Track 1: benchmark discrimination.

Compute MPI on a benchmark family of structurally diverse systems, first in structural-only mode and then, where data permit, in structural-plus-dynamic mode. MPI should yield distinct score profiles and seam maps across architectural families, and those distinctions should not collapse into trivial correlates of size, density, or degree heterogeneity.

Track 2: structural–dynamic link.

Test whether higher MPI predicts stronger realized spectral integration in measured data, by comparing structural MPI diagnostics with realized Φ -spectral measures from EEG, MEG, LFP, simulation,

or other time-series sources. The central hypothesis is envelope-setting: morphology constrains the space of dynamical integration that is realistically accessible.

Track 3: trace and temporal predictions.

Test whether systems with higher s_{trace} and s_{temp} exhibit stronger trace-supported dynamics, more stable internal clock signatures, or more durable record-supported basins. The operationalization will vary by domain, but the research question is stable: does morphology predict where robust trace formation and temporally ordered organization are likely to appear?

Track 4: AI alignment, safety, and control relevance.

For AI-facing benchmarks, an additional question is whether particular MPI profiles correlate with alignment-relevant failure modes. One can ask whether low s_{int} combined with high s_{multi} predicts seam-sensitive internal conflict in modular systems, whether high s_{trace} combined with weak s_{rob} predicts susceptibility to telemetry or trace poisoning, and whether strong s_{temp} predicts forms of lock-in that become difficult to reverse once persistent records accumulate.

Across tracks, ablations are important. Lesioning seam edges, removing trace layers, perturbing phase structure, and altering coarse-graining choices should produce predicted subscore drops in the expected direction. If MPI is to function as a structural prior, its components must track the right failures when the architecture is deliberately degraded.

12. Limitations

MPI is deliberately architectural, and its limitations follow from that choice. Morphology can be over-read: some systems will be dominated by microphysical details that a coarse hypergraph fails to capture, while others may be poorly represented by the chosen degrees of freedom or layer decomposition. Calibration matters: the logistic transforms and weighting conventions proposed here are placeholders until benchmark corpora are broad enough to support principled tuning (Section 8.1). The resonant-mode component is a proxy unless higher-tier data are available; it should not be mistaken for a direct quantum indicator. The contextual patchiness module depends on a defensible predicate family and remains more modeling-sensitive than the core bundle. The trace-geometry subscore requires a partition into core and trace nodes that is itself a nontrivial modeling choice in novel domains. Finally, MPI does not solve the sufficiency problem: an architecture may look promising and still fail to realize the relevant dynamics.

These limitations define MPI's scope: it is a structural prior whose value lies in ranking architectures, localizing bottlenecks, and connecting morphology to later dynamical work—not in replacing it.

13. Conclusions

Morphology deserves to be treated as a comparative variable in its own right, not merely as a backdrop for dynamical analysis. It is motivated in part by current work on spectral integration and by the QDT/PT family of ideas, but its use is broader than any one interpretive program. The underlying thought is straightforward: before asking whether a system realizes the right dynamics, ask whether its architecture could support them.

MPI makes that question operational by representing morphology as a constraint hypergraph, scoring core features through a bundle rather than a single scalar, and treating seam topology, trace geometry, temporal scaffolding, and robustness as first-class outputs. Its value lies in helping decide where to look, what to perturb, and how to compare architectures whose control logic, record structure, and temporal organization differ substantially.

For AI safety, MPI raises a question that often appears too late in evaluation pipelines: before a system is called interpretable, corrigible, or safe to scale, does its architecture make those properties plausible? Seam maps, trace geometry, multiscale seam persistence, and temporal scaffolding do not

settle that question on their own, but they can narrow the search space, localize likely bottlenecks, and indicate where decay mechanisms, interface controls, or additional oversight are most needed.

Appendix A. Toy Benchmark Construction Details

This appendix provides construction details for the three toy systems summarized in Table A1. All computations use the structural-only pipeline with illustrative sigmoid coefficients and Tier-0 proxies for s_{res} . Raw seam diagnostics are reported alongside normalized subscores.

Table A1. MPI profiles for three toy architectures (illustrative sigmoid coefficients; raw diagnostics reported for independent verification). MPI_{tot} is a conjunctive bundle score indicating whether an architecture scores nontrivially on *all* core dimensions at once. The centralized toy has high s_{int} but $s_{\text{multi}} \approx 0$ because it lacks nontrivial multiscale hierarchy, which collapses MPI_{tot} via the geometric mean. The federated system shows low global integration but strong multiscale nesting, moderate trace geometry, and broader temporal scaffolding. The stigmergic system is weakest on resonant-mode support and trace geometry, consistent with its sparse, tree-like topology.

	Centralized (hub-and-spoke)	Federated (octopus-like)	Stigmergic (mycelium-like)
$ V , E $	9, 16	49, 136	300, 332
Φ_{cond}	0.875	0.010	0.016
λ_2	0.882	0.010	0.002
s_{int}	0.565	0.273	0.466
s_{multi}	~ 0	0.944	0.302
s_{res} (Tier 0)	0.57	0.54	0.261
s_{trace}	0.69	0.55	0.232
s_{temp}	0.48	0.61	0.52
s_{rob}	0.348	0.329	0.465
MPI_{tot}	0.00	0.34	0.33

Appendix A.1. Minimal Centralized Hub-and-Spoke Toy

Construction.

A single central hub node is connected with strong edges (weight 10) to each of 8 peripheral nodes. Peripheral nodes are connected to their two nearest neighbors with moderate edges (weight 3), forming a ring ($|V| = 9, |E| = 16$). This is a synthetic centralized-control toy included to provide a contrast case for strongly integrated hub-dominated architectures.

Trace partition.

Four peripheral nodes are designated as V_{trace} (representing readout or interface surfaces); the hub and remaining peripherals form V_{core} .

Key diagnostics.

$\Phi_{\text{cond}} = 0.875$ and $\lambda_2 = 0.882$ indicate strong resistance to balanced decomposition. However, the graph is too small and uniform for a nontrivial coarse-graining hierarchy: spectral clustering at any resolution above 2 clusters produces trivial or unstable partitions. This drives $s_{\text{multi}} \approx 0$, which collapses MPI_{tot} via the geometric mean. The profile correctly reflects strong unity topology alongside absent multiscale depth.

Appendix A.2. Federated (Octopus-like) Toy

Construction.

A central hub is connected to 8 arm modules, each consisting of 6 internally strongly connected nodes (intra-arm weight 8). Arm-brain connections use moderate weight (2). A weak circumoral ring (weight 0.5) connects neighboring arm bases ($|V| = 49, |E| = 136$).

Trace partition.

The tip node of each arm plus the central hub form V_{trace} (9 nodes); all other nodes are V_{core} .

Key diagnostics.

Global conductance is very low ($\Phi_{\text{cond}} = 0.010$): the weakest balanced cut separates arms from the brain with minimal coupling loss, driving s_{int} down as expected for a federated architecture. Multiscale nesting is strong ($s_{\text{multi}} = 0.944$): the arm-module structure reappears coherently at every coarse-graining level. Trace capacity is moderate because each core node can reach trace nodes via at most 2–3 edge-disjoint paths, and trace concentration is diffuse across 9 distributed trace nodes.

Remark A1 (Quotient invariance). *If the 8 arms are treated as interchangeable (i.e., one imposes cyclic or full permutation symmetry), partition stability improves dramatically: the median variation of information across bootstrap replicates drops from ~ 1.1 to ~ 0 [15]. MPI reports should state explicitly whether such symmetries were imposed.*

Appendix A.3. Stigmergic (Mycelium-like) Toy

Construction.

A branching network with 300 nodes is generated by a stochastic growth model (extension probability 0.85, branching probability 0.15). Anastomosis (hyphal fusion) is added by connecting random nearby non-adjacent node pairs with probability proportional to inverse distance, producing 332 edges. All edge weights are 1.

Trace partition.

Tip nodes (degree 1) are designated as V_{trace} ; all interior nodes are V_{core} .

Key diagnostics.

The network is sparse and predominantly tree-like. Cycle-richness is low ($C_{\text{cycle}} = 0.11$), yielding weak s_{res} . Trace capacity is modest: many core nodes have only 1–2 disjoint paths to tip traces, and the trace set is large but poorly connected to the interior. Temporal breadth (B_{τ}) is moderate, reflecting a spread of Laplacian eigenvalues from near-zero (long trunk diffusion times) to moderate values (short anastomosis-loop recurrence). Robustness is the strongest subscore: the dominant trunk structure is hard to disrupt.

Appendix A.4. Profile Comparison

Each architecture produces a recognizably distinct MPI signature. The centralized system is integration-strong but multiscale-degenerate. The federated system is integration-weak but multiscale-rich with distributed traces. The stigmergic system is uniformly moderate-to-weak, with relative strength in robustness and temporal breadth. These distinctions track genuine architectural contrasts—hub-and-spoke vs. modular-federated vs. sparse-branching—rather than trivial graph statistics such as density or size.

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