

Convergence by Composition

A Structured Adapter Architecture for Multi-Agent System Integration

Preprint – Feedback Welcome

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Abstract

Agent orchestration frameworks—Swarms, DeerFlow, AnimaWorks, Ralph, and A-Evolve—make fundamentally different architectural choices (graph-based, event-driven, hierarchical, evolutionary) yet share structural concerns: error amplification across handoffs, coordination overhead from tool proliferation, and the absence of convergence guarantees for adaptive loops. We present a structured adapter architecture centred on a single intermediate representation, **ExternalTopology**, that lets Operon’s structural analysis layer analyze the static structural skeleton of external agent configurations without importing the target framework. Six adapters parse framework-specific configurations into this common representation; four epistemic bounds serve as a structural linter; four TLA+ specifications verify safety invariants; and a co-design fixed-point proof (following Zardini) establishes that the adaptive assembly loop converges within ε . The architecture is implemented in 23 convergence modules with 308 convergence-specific unit tests as part of a broader suite of 1,530 tests and 107 worked examples.

1 Introduction

The past two years have seen a proliferation of agent orchestration frameworks, each embodying a different theory of how autonomous agents should coordinate. Swarms [6] provides graph-based workflows with sequential, concurrent, and hierarchical scheduling. DeerFlow, built on LangGraph, offers sub-agent harnesses with sandboxed execution and progressive skill loading. AnimaWorks [1] introduces developmental priming with heartbeat-driven memory consolidation. Ralph organizes agents as “hats” connected by event-driven transitions with backpressure constraints. A-Evolve implements an evolutionary Solve–Observe–Evolve–Gate–Reload loop that mutates workspace snapshots under a fitness gate.

These frameworks differ in execution model, memory architecture, and deployment infrastructure, yet they converge on a shared set of structural concerns. Every multi-agent system must manage error amplification across sequential handoffs, balance coordination overhead against parallel speedup, and decide when an adaptive loop has stabilized. As Evans, Bratton, and Agüera y Arcas argue, intelligence is “fundamentally plural, social, and relational” [4]; the engineering challenge is to build, verify, and optimize the structural infrastructure for such systems.

The Agentic Computation Graph (ACG) survey by Yue et al. [7] provides a comprehensive taxonomy of workflow optimization methods—from static template search to in-execution editing—but does not address formal verification or compositional convergence proofs. Kim et al. [5] identify scaling laws for agent systems whose functional form is consistent with the epistemic bounds derived in the present work.

Our contribution is a *structured adapter architecture* that decouples structural analysis from runtime execution:

1. **ExternalTopology** as a framework-agnostic intermediate representation: six adapters parse six frameworks into a single frozen dataclass; all downstream analysis is source-agnostic.
2. **Epistemic bounds as structural linter**: the adapter risk score combines error amplification, sequential penalty, and tool density bounds with a topology-mismatch flag; parallel acceleration is available from the epistemic layer but not included in the adapter’s composite score.
3. **TLA+ verified safety invariants**: four specifications cover template exchange, developmental gating, convergence detection, and evolution gating, verified by the TLC model checker with small-model parameters.
4. **Co-design convergence**: each adapter is a design problem in Zardini’s co-design theory [8]; series/parallel composition and feedback fixed-point iteration prove that scoring stabilizes.

The rest of this paper describes the architecture (Section 2), formal results (Section 3), implementation (Section 4), related work (Section 5), discussion (Section 6), and conclusion (Section 7).

2 Architecture

The convergence architecture is a five-layer stack (Figure 1). Each layer is independently useful: the cognitive layer can run without an orchestration layer; the structural layer can analyze topologies without executing them.

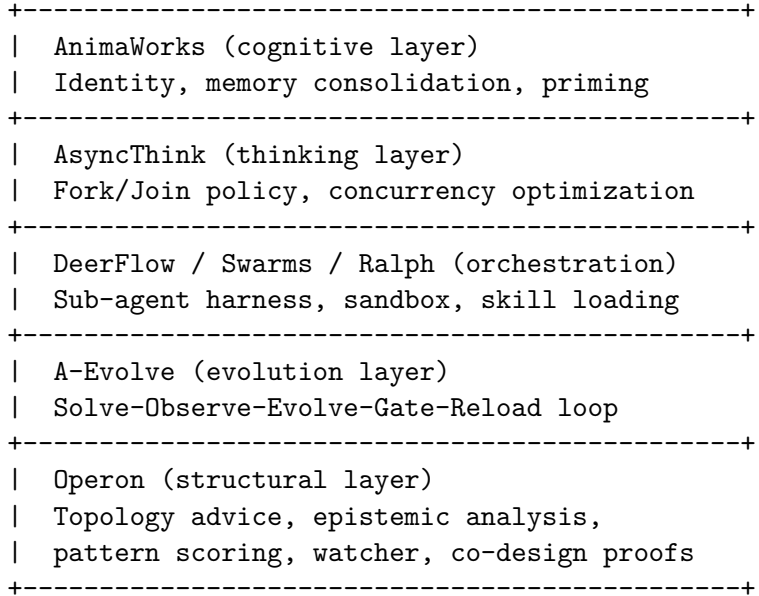


Figure 1: Five-layer convergence stack. Operon sits at the bottom, providing structural analysis to every layer above. Arrows flow upward (analysis results) and downward (topology descriptions).

2.1 ExternalTopology as Framework-Agnostic Intermediate Representation

The key abstraction is a single frozen dataclass that every adapter produces and every analysis function consumes:

Listing 1: ExternalTopology dataclass (convergence/types.py).

```
@dataclass(frozen=True)
class ExternalTopology:
    source: str # "swarms"|"deerflow"|...
    pattern_name: str
    agents: tuple[dict[str, Any], ...]
    edges: tuple[tuple[str, str], ...]
    metadata: dict[str, Any] = field(default_factory=dict)
```

The agent specs use `dict[str, Any]` to accommodate heterogeneous framework configurations. Python type hints annotate the top-level fields; the nested dicts carry no schema enforcement at runtime. The `@dataclass(frozen=True)` decorator prevents reassignment of top-level fields but does not deep-freeze nested mutable objects. The `source` field is a tag, not a type discriminant—all downstream code treats every `ExternalTopology` identically. Agents are plain dicts with at least `name` and `role` keys; edges are directed pairs. This representation is serializable as JSON, enabling analysis results to be stored, transmitted, and compared across framework boundaries.

2.2 Analysis Pipeline

The function `analyze_external_topology(topology)` takes any `ExternalTopology` and returns an `AdapterResult`:

Listing 2: AdapterResult dataclass (convergence/types.py).

```
@dataclass(frozen=True)
class AdapterResult:
    topology_advice: TopologyAdvice
    suggested_template: PatternTemplate | None
    warnings: tuple[str, ...]
    risk_score: float # [0.0, 1.0]
```

The pipeline constructs a wiring diagram from agents and edges, applies three epistemic bounds (error amplification, sequential penalty, tool density) plus a topology-mismatch flag, generates structural warnings, and optionally produces a `PatternTemplate` for the pattern library.

2.3 Design Principles

Three principles govern the adapter architecture:

1. **Serializable dicts, zero external imports.** Every adapter operates on plain dicts parsed from configuration files or API responses. No adapter imports `Swarms`, `DeerFlow`, `AnimaWorks`, `Ralph`, or `A-Evolve`.
2. **One parser, one analyzer.** Adding a new framework means writing one `parse_*` function that produces `ExternalTopology`; the analysis code is unchanged.
3. **Bidirectional exchange.** `DeerFlow`’s Markdown skill files convert to `PatternTemplate` and vice versa, enabling cross-framework template sharing.

3 Formal Results

3.1 Epistemic Theorems as Structural Linter

Operon derives four structural bounds from epistemic topology—the study of how knowledge and uncertainty propagate through agent communication graphs. These bounds are applied to every `ExternalTopology` as a “structural linter,” flagging architectures that are likely to amplify errors or incur excessive coordination overhead.

Definition 1 (Error Amplification Bound). *For a sequential chain of n agents, each with per-stage error rate ϵ , the cumulative error probability is bounded by:*

$$P_{\text{error}}(n) \leq 1 - (1 - \epsilon)^n$$

When $n\epsilon \ll 1$, the linear approximation $P_{\text{error}} \approx n\epsilon$ applies. The linter warns when the chain depth produces $P_{\text{error}} > \tau$ for a configurable tolerance τ .

Definition 2 (Sequential Penalty). *For a topology with n_{seq} sequential handoffs and total agent count N , the sequential penalty ratio is:*

$$\rho_{\text{seq}} = \frac{n_{\text{seq}}}{N}$$

Values of $\rho_{\text{seq}} > 0.7$ indicate that the topology is predominantly sequential and may benefit from parallelization.

Definition 3 (Parallel Acceleration). *For a topology with k independent branches of depths d_1, \dots, d_k , the critical-path latency under parallel execution is:*

$$L_{\text{par}} = \max_{i \in [k]} d_i$$

The speedup over sequential execution is $S = \sum_i d_i / L_{\text{par}}$. The linter reports the achievable speedup and flags topologies where $S < 1.2$ (parallel structure exists but provides negligible benefit).

The full epistemic analysis layer computes all four metrics. The `analyze_external_topology()` function exposes three of these (error amplification, sequential penalty, tool density) plus a topology-mismatch flag in the composite risk score. Parallel acceleration is computed and reported separately but not included in the risk score.

Definition 4 (Tool Density). *For a topology with T distinct tools across N agents, the tool density is $\delta = T/N$. High density ($\delta > 3$) suggests coordination overhead: each agent must manage many tool interfaces. Low density ($\delta < 0.5$) suggests under-utilization.*

The composite risk score is a weighted sum of four components:

$$r = 0.4 \hat{P}_{\text{error}} + 0.3 \rho_{\text{seq}} + 0.2 \delta_{\text{density}} + 0.1 M_{\text{topo}}$$

where \hat{P}_{error} is the normalized centralized error bound, ρ_{seq} is the effective sequential overhead, δ_{density} is the normalized planning-cost ratio (tool density), and $M_{\text{topo}} \in \{0, 1\}$ is a binary topology-mismatch flag raised when the detected topology class diverges from the recommended class. The weights are $w_1 = 0.4$, $w_2 = 0.3$, $w_3 = 0.2$, $w_4 = 0.1$.

These bounds are consistent with the scaling laws reported by Kim et al. [5]: their empirical observation that error rates grow with chain depth and that coordination overhead dominates at high agent counts corresponds to the Error Amplification and Tool Density bounds respectively.

3.2 TLA+ Verified Safety Invariants

Four TLA+ specifications model critical protocols in the convergence architecture. Each is verified by the TLC model checker with small-model parameters (2–3 agents, 2–3 templates/tools, bounded iteration counts). TLC model configurations (`.cfg` files) with small-model parameters and a step-by-step reproduction guide are provided in the `specs/` directory alongside the specifications. Table 1 summarizes the specifications and their key invariants.

Table 1: TLA+ specifications and verified safety properties.

Specification	Key Safety Invariants	Actions
TemplateExchangeProtocol	Adoption respects <code>min_stage</code> Trust changes only via <code>RecordOutcome</code> No self-adoption	Export, Import, RecordOutcome, StageAdvance
DevelopmentalGating	Critical periods never reopen Stages monotonically advance Tools respect capability gates	Tick, AcquireTool, OpenPeriod, ClosePeriod, Scaffold
ConvergenceDetection	Halt is terminal Intervention rate triggers halt	StageResult (with nondeterministic intervention)
EvolutionGating	Score monotonically non-decreasing Workspace advances only via Gate Version bounded by <code>MAX_VERSIONS</code>	Evolve, Gate, Rollback

TemplateExchangeProtocol. Models cross-agent template sharing with trust-weighted adoption. An agent imports a peer’s template only when three guards are satisfied: (i) the agent’s developmental stage meets the template’s minimum stage, (ii) trust in the peer exceeds `MIN_TRUST`, and (iii) the effective score $\text{peer_success_rate} \times \text{trust} \geq \text{ADOPTION_THRESHOLD}$. Trust updates use exponential moving average (EMA) smoothing, applied exclusively in the `RecordOutcome` action—all other actions leave trust unchanged, a structural encoding of the invariant.

DevelopmentalGating. Models lifecycle progression with critical periods and capability gating. Agents progress through lifecycle stages, advancing through four stages (Embryonic \rightarrow Juvenile \rightarrow Adolescent \rightarrow Mature). The key safety property is *critical period irreversibility*: once a period transitions from “open” to “closed,” it can never reopen. This models time-limited configuration windows that close permanently.

ConvergenceDetection. Models the watcher’s convergence protocol. As agents execute stages, the watcher tracks the ratio of interventions (RETRY, ESCALATE, HALT) to completed stages. When this ratio exceeds `MAX_RATE`, the agent is halted in the same atomic step—a safety property expressing that non-convergent execution is always detected and terminated.

EvolutionGating. Models the A-Evolve mutation loop. The `Gate` action accepts a pending mutation only when its benchmark score meets or exceeds the current score plus `MIN_IMPROVEMENT`. This ensures monotonic score progression: the agent system never regresses. The specification intentionally provides no liveness guarantee, since evolution liveness depends on the score generator—an external assumption outside the structural model.

3.3 Co-Design Convergence

We apply a simplified version of Zardini’s co-design framework [8], using ordinary function composition rather than the full categorical apparatus. We model each adapter as a *design problem* (DP)—a monotone map from a resource poset to a functionality poset. Monotonicity means that more resources yield at least as many functionalities.

Definition 5 (Design Problem). *A design problem is a pair (f, g) where $f : \mathcal{R} \rightarrow \mathcal{F}$ maps resources to functionalities and $g : \mathcal{R} \rightarrow \{0, 1\}$ is a feasibility predicate. The map f is monotone: $r_1 \leq r_2 \implies f(r_1) \leq f(r_2)$.*

Definition 6 (Series Composition). *Given design problems DP_1 and DP_2 , their series composition $DP_1 \rightarrow DP_2$ is defined by $f_{1 \rightarrow 2}(r) = f_2(f_1(r))$, with feasibility $g_{1 \rightarrow 2}(r) = g_1(r) \wedge g_2(f_1(r))$.*

Definition 7 (Parallel Composition). *The parallel composition $DP_1 \parallel DP_2$ is defined by $f_{1 \parallel 2}(r) = f_1(r) \cup f_2(r)$, with feasibility $g_{1 \parallel 2}(r) = g_1(r) \wedge g_2(r)$.*

The full adapter stack is a series composition: parsing \rightarrow analysis \rightarrow template generation \rightarrow scoring. The adaptive assembly loop (run \rightarrow record \rightarrow score \rightarrow select) is feedback composition, where the output of the scoring step feeds back as input to the next iteration’s selection.

Theorem 1 (Adaptive Loop Approximate Convergence). *Let DP be the feedback composition of the adapter stack, with scoring function $s : \mathcal{F} \rightarrow [0, 1]$ and feedback map $\phi(r, f) = r \cup \{s(f)\}$. If s is monotone, then the sequence s_0, s_1, s_2, \dots is monotone nondecreasing and bounded above by 1. For any $\varepsilon > 0$, the implementation terminates when $|s_{n+1} - s_n| < \varepsilon$ or after a configurable maximum number of iterations.*

Proof. The scoring function s maps functionalities to $[0, 1]$. The feedback map ϕ is monotone by composition of monotone maps. Therefore the sequence $s_0 \leq s_1 \leq s_2 \leq \dots$ is monotone nondecreasing and bounded above by 1, so it converges to $\sup_n s_n = s^*$ by the monotone convergence theorem. The implementation’s `feedback_fixed_point()` has two termination modes: (1) when $|s_{n+1} - s_n| < \varepsilon$ (default 0.01) for the monitored scoring key, the implementation reports `converged=True`, indicating the tracked value has stabilized within ε ; (2) when the iteration count reaches the safety bound (default 100) without satisfying the ε criterion, the algorithm halts with `converged=False` and returns the last computed state. The mathematical guarantee (monotone convergence) ensures the sequence approaches s^* ; the implementation provides a practical decision procedure that reports whether that convergence was achieved within the allocated budget. \square

The implementation in `convergence/codesign.py` provides `compose_series`, `compose_parallel`, and `feedback_fixed_point` with the exact convergence semantics described above.

4 Implementation

The convergence architecture is implemented in 23 Python modules under `operon_ai/convergence/`, tested by 308 convergence-specific unit tests as part of a broader suite of 1,530 tests across the entire Operon codebase. Table 2 summarizes the six adapters.

4.1 Bidirectional DeerFlow Skill Bridge

DeerFlow’s Markdown-based skill system is structurally similar to Operon’s `PatternTemplate`: both represent reusable workflow patterns with metadata and staged execution steps. The module

Table 2: Convergence adapters: source frameworks and key functions.

Adapter	Source	Parse Function	Template Function
Swarms	Graph workflows	<code>parse_swarm_topology</code>	<code>swarm_to_template</code>
DeerFlow	LangGraph sessions	<code>parse_deerflow_session</code>	<code>deerflow_to_template</code>
AnimaWorks	Supervisor configs	<code>parse_animaworks_org</code>	<code>animaworks_to_template</code>
Ralph	Hat orchestration	<code>parse_ralph_config</code>	<code>ralph_to_template</code>
A-Evolve	Workspace manifests	<code>parse_aevolve_workspace</code>	<code>aevolve_to_template</code>
Scion	Grove configs	<code>parse_scion_grove</code>	<code>scion_to_template</code>

`convergence/deerflow_skills.py` provides bidirectional conversion: `skill_to_template` parses DeerFlow Markdown skills (extracting frontmatter, workflow steps, and tool references) into scored `PatternTemplate` instances, while `template_to_skill` exports Operon templates as DeerFlow-compatible Markdown. This enables cross-framework template exchange: Operon can import DeerFlow’s community-contributed skill library, and DeerFlow can consume Operon’s structurally validated templates.

4.2 Hybrid Assembly

The `hybrid_skill_organism` function implements a two-phase assembly strategy. In the first phase, it queries the pattern library for templates matching the task fingerprint; if a template with a sufficiently high success score exists, it is used directly. In the second phase (fallback), an LLM generator produces a one-shot agent configuration, which is registered in the library for scoring refinement over subsequent runs. This library-first, generator-fallback design ensures that the system improves with experience while maintaining availability for novel tasks.

4.3 Cognitive Extensions

Three modules extend the cognitive layer:

- **PrimingView** (in `patterns/priming.py`): a subclass of `SubstrateView` that adds recent outputs, telemetry, experience records, and developmental status as multi-channel context.
- **HeartbeatDaemon** (in `patterns/heartbeat.py`): periodic consolidation of short-term observations into long-term memory, inspired by AnimaWorks’ heartbeat protocol.
- **AsyncOrganizer** (in `convergence/async_thinking.py`): Fork/Join execution within individual stages, inspired by the AsyncThink [3] observation that intra-stage parallel reasoning can reduce latency without increasing token cost.

4.4 Catalog Seeding

The `convergence/catalog.py` module seeds the pattern library from multiple sources: `seed_library_from_swarm` registers built-in Swarms workflow patterns; `seed_library_from_deerflow` imports DeerFlow skills; `seed_library_from_ralph` converts Ralph hat configurations; and `seed_library_from_acg_survey` registers templates from the ACG survey’s comparison cards [7], annotated with graph determination time and plasticity mode metadata. The combined catalog provides a rich initial library for hybrid assembly.

5 Related Work

Agent workflow taxonomy. The ACG survey by Yue et al. [7] provides a comprehensive taxonomy of workflow optimization methods, classifying approaches along two dimensions: graph determination time (offline, pre-execution, in-execution) and graph plasticity mode (static, dynamic). Our work operates within this taxonomy: the adapter architecture is a pre-execution analysis layer, while the watcher provides in-execution monitoring. The ACG framework treats workflow graphs as optimizable structures; we add formal verification and convergence guarantees that the survey identifies as open problems.

Plural intelligence. Evans et al. [4] argue that the next advance in AI will be combinatorial societies of specialized agents rather than monolithic models, drawing on primate social scaling and cultural ratchet effects. Our work provides the formal infrastructure—structured composition, verified safety invariants, convergence proofs—for the “plural intelligence” vision they articulate.

Scaling laws. Kim et al. [5] derive empirical scaling laws for multi-agent systems, finding that error rates grow with chain depth and coordination overhead dominates at high agent counts. These findings are consistent with our epistemic bounds: the Error Amplification Bound predicts the chain-depth dependence; the Tool Density bound predicts the coordination overhead curve.

Intra-stage reasoning. Chi et al.’s AsyncThink [3] demonstrates that allowing agents to reason asynchronously within a stage—forking parallel thought branches and joining at a synchronization point—reduces latency without increasing token cost. Our `AsyncOrganizer` formalizes this pattern with configurable concurrency ratios and critical-path scheduling.

Co-design theory. Zardini [8] develops a general theory of co-design based on monotone maps between resource and functionality posets, with series, parallel, and feedback composition operators. We apply this framework to model each adapter as a design problem and prove that the adaptive assembly loop converges to a fixed point.

6 Discussion and Future Work

From analysis to compilation. The current adapter architecture analyzes structure but does not generate executable workflows. The natural next step is *compilers*: functions like `organism_to_swarms` and `organism_to_deerflow` that compile Operon agent systems into Swarms workflow configurations or DeerFlow LangGraph sessions. For DeerFlow, the deepest integration is a native LangGraph watcher node (`operon_watcher_node`) that provides real-time structural monitoring inside DeerFlow’s execution loop. A Ralph compiler (`organism_to_ralph`) would emit hat configurations with backpressure constraints derived from the epistemic analysis.

Cross-target evaluation. A systematic evaluation harness running identical tasks across Operon, Swarms, DeerFlow, AnimaWorks, and Ralph would provide empirical validation of the structural predictions. The ACG survey’s recommendation to measure structural variation across inputs is a valuable addition to such an evaluation protocol, alongside standard metrics (success rate, token cost, latency, intervention count, convergence rate).

Prompt optimization. The adapter architecture optimizes topology but leaves node-level content (prompts, demonstrations) fixed. DSPy-style prompt optimization integrated via the A-Evolve mutation loop could address this gap: the evolutionary Solve–Observe–Evolve–Gate–Reload cycle naturally accommodates prompt mutations as a special case of workspace evolution, with the fitness gate ensuring monotonic improvement.

Limitations. The adapters analyze structure, not runtime behavior. An architecture that scores well on all four epistemic bounds may still fail due to prompt quality, model capability, or environmental non-stationarity. The TLA+ specifications are verified with small-model parameters; scaling to production-size state spaces would require compositional verification techniques or abstraction refinement. The co-design convergence proof assumes monotonicity of the scoring function, which may not hold under distribution shift in the task stream.

7 Conclusion

We have presented a structured adapter architecture for integrating Operon’s structural analysis layer with five external agent orchestration systems—Swarms, DeerFlow, AnimaWorks, Ralph, and A-Evolve—through a single intermediate type, `ExternalTopology`. The architecture contributes four epistemic bounds that serve as a structural linter, four TLA+-verified safety invariants, and a co-design convergence proof showing that the adaptive assembly loop stabilizes within ϵ . By operating on serializable dicts with zero external imports, the adapter architecture achieves framework-agnostic analysis while preserving a structured interchange format with top-level frozen dataclass fields (nested dicts remain mutable by Python convention). The 23 convergence modules, 308 convergence unit tests, 4 TLA+ specifications, and 107 worked examples provide a concrete, verifiable foundation for multi-agent system integration.

8 Empirical Validation of Structural Guarantees

The preceding sections establish a theoretical framework for structural analysis across agent orchestration systems. This section provides empirical grounding: three benchmarks testing whether Operon’s biologically-grounded structural guarantees deliver measurable benefits over simpler alternatives. Full methodology and detailed results are presented in a companion paper [2]; here we summarize the findings and their implications for the adapter architecture.

8.1 Benchmark Suite Design

Each benchmark compares three variants: *Biological* (full Operon feature), *Ablated* (feature disabled), and *Naïve* (simple non-biological alternative). All benchmarks run $N = 1,000$ trials per seed across 10 seeds (10M+ total data points), with Wilson 95% confidence intervals. No LLM calls are made during execution.

Three features are tested, chosen for their relevance to the adapter architecture’s structural claims:

1. **Metabolic priority gating:** `ATP_Store + MTORScaler` vs. flat budget counter. Tests resource management in orchestrated workflows.
2. **Quorum sensing:** `QuorumSensingBio` (autoinducer accumulation with temporal decay) vs. majority voting. Tests leaderless consensus in multi-agent topologies.

3. **Epiplexity stagnation detection:** `EpiplexityMonitor` (Bayesian two-signal) vs. cosine similarity. Tests convergence monitoring in adaptive loops.

8.2 Results Summary

Metabolism: clear win. Under bursty load, the biological system served 100% of critical operations (priority ≥ 5) during resource pressure, versus 39.8% for the flat counter ($\Delta = +0.602$, $p < 0.001$, $N = 24,139$ pressure events). Against the naive baseline, the biological system also improves total throughput (71.9% vs 68.5% under bursty load). Both biological and ablated variants achieve identical critical-service rates; the mTOR scaler’s additional preemptive gating reduces gradual-depletion throughput by 1.7 percentage points (97.9% vs 99.6%) without providing further critical-service benefit in these experiments.

Quorum sensing: precision–recall tradeoff. The biological signal-accumulation model achieved 0% false-positive rate across all configurations with 71–87% true-positive rate at 40% agent compromise. Majority voting achieved 0% FPR but near-0% TPR. Independent detection achieved near-100% TPR but 5–18% FPR. The biological model occupies a unique operating point unreachable by either alternative.

Epiplexity: embedding-dependent. With mock embeddings, the naive cosine-similarity detector outperformed the biological Bayesian two-signal design on detection accuracy. A follow-up experiment with real sentence embeddings (all-MiniLM-L6-v2) reversed the finding: the biological monitor achieved 96% accuracy on convergence and false-stagnation scenarios versus 2–40% for the naive detector, which false-alarmed on 98% of converging steps. The two-signal design’s convergence/stagnation discrimination—its core structural guarantee—activates only when the embedding signal carries semantic meaning.

8.3 Revised Framework-Fit Analysis

The benchmark results ground the adapter architecture’s claims about which frameworks benefit most from Operon’s structural layer.

A-Evolve. Metabolic budgets directly address the unbounded-exploration failure mode in its Solve-Observe-Evolve-Gate-Reload loop. The benchmark confirms that the fitness gate (a critical operation) is always evaluated under metabolic budgeting, even when exploration budget is depleted. This maps to A-Evolve’s quality gate never being skipped.

Swarms. Quorum sensing provides leaderless consensus across graph-based agent topologies. The 0% false-positive rate is operationally critical for Swarms: false consensus triggering coordinated action across a swarm is more costly than a missed detection. Morphogen-gradient coordination (not benchmarked) provides additional theoretical fit for gradient-based specialization.

DeerFlow. Metabolic budgets prevent recursive sub-agent calls from exhausting resources. The MTORScaler’s rate-of-change sensitivity is relevant for DeerFlow’s progressive skill loading, where resource consumption can accelerate during deep recursion.

AnimaWorks. Genome immutability provides configuration audit (a structural guarantee by construction, not requiring benchmarking). The immune system’s role-manipulation detection relates to quorum sensing’s adversarial consensus problem.

Ralph. Metabolic budgets map to backpressure enforcement in Ralph’s event-driven architecture. The metabolic state machine’s priority gating translates to event-priority filtering under resource pressure.

Scion. Quorum sensing enables consensus across containerized isolation boundaries. Signal decay naturally handles container lifecycle events—signals from terminated containers age out without explicit cleanup.

9 Epistemic Topology: Scope and Limitations

9.1 What Epistemic Topology Provides

The four epistemic bounds (Section 3.1) serve as a structural linter for the adapter architecture. The error amplification bound identifies topologies that expand the failure surface. The sequential communication penalty flags long pipelines with high handoff cost. The parallel speedup bound identifies bottleneck layers. The tool density ratio flags planning overhead from distributed tool access.

Together, these bounds produce the adapter risk score used by `analyze_external_topology()` to flag architectures likely to exhibit structural failure modes. This diagnostic function has proven useful in practice: it correctly identifies that a 20-agent Swarms pipeline has higher sequential overhead than a 5-agent DeerFlow hierarchy, and that centralizing tools on a single agent reduces planning overhead at the cost of creating a single point of failure.

9.2 Current Limitations

No runtime feedback loop. The epistemic layer computes static bounds from topology structure. It does not reconfigure topology at runtime based on observed behavior. `analyze_external_topology()` is called once per configuration, not per execution step. The adapter tells you the risk is high; it does not automatically restructure the topology to reduce it.

No empirical validation of predicted bounds. The four theorem bounds have been checked for qualitative consistency with architecture-level scaling laws [5], but not against Operon’s own benchmark results. The metabolism and quorum sensing benchmarks (Section 8) validate *mechanism-level* guarantees; the topology-level bounds remain validated only by external consistency checks.

Diagnostic, not prescriptive. The risk score identifies structural risk factors but does not prescribe remediation. A topology flagged as high-risk for error amplification receives no suggestion for how to restructure.

9.3 Relationship to Mechanism Benchmarks

The epistemic topology and the biological mechanism benchmarks operate at different levels of the architecture. Topology-level bounds predict coordination costs (a long pipeline *will* accumulate

sequential overhead). Mechanism-level guarantees prevent specific failure modes (critical operations *will* be served under pressure).

The two are complementary: epistemic topology identifies architectures *likely to need* structural guarantees; the mechanism benchmarks validate that those guarantees *work as claimed*. Both are necessary for a complete structural analysis: topology without mechanisms identifies problems without providing solutions; mechanisms without topology provides solutions without knowing which problems to solve.

9.4 Recommendation

Epistemic topology should be retained as a structural analysis tool. Its diagnostic value—identifying high-risk architectures before deployment—is well-supported by the adapter framework’s design. However, claims about the predictive precision of the four bounds should be tempered until empirical validation against measured benchmark performance is completed. Future work should compare predicted error amplification and sequential overhead against actual measured performance across different topologies running identical task suites.

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