Murmuration: Kondo-Mediated Collective Stability and Adaptive Relaxation in Multi-Agent Systems

Collaborative Research Framework: Human–AI Synthesis

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Abstract

Traditional Artificial Intelligence architectures frequently oscillate between catastrophic forgetting and excessive rigidity when exposed to environmental novelty. We propose a physics-inspired framework, termed *Murmuration*, which models intelligence as a phase of mediated stability rather than as task performance or statistical inference. Motivated by the Kondo necklace model in condensed-matter physics, the framework treats adaptive behavior as the regulation of internal structure through distributed interaction. This perspective enables collective systems to absorb perturbations, relax excess coherence, and recover stable operation without centralized control.

1 Introduction

Contemporary artificial intelligence systems are predominantly constructed around large-scale optimization procedures applied to static objective functions. While such systems can achieve high accuracy within fixed distributions, they remain structurally fragile under sustained novelty, adversarial perturbation, or abrupt environmental change. Empirically, these failures manifest in two dominant regimes: rapid destabilization, commonly described as catastrophic forgetting, and excessive stabilization, commonly described as overfitting or rigidity. These behaviors suggest that current architectures lack an intrinsic mechanism for regulating internal structure under disturbance.

By contrast, many natural systems exhibit collective resilience without centralized coordination or explicit optimization. Flocking birds, schooling fish, neural populations, and certain condensed-matter systems maintain coherent organization despite continuous perturbation. Their stability arises not from prediction accuracy or global supervision, but from local interactions that mediate disturbance across the system. This observation motivates a redefinition of intelligence grounded in physical stability rather than behavioral performance.

In this work, intelligence is treated as a control property: the ability of a system to maintain bounded internal structure in the presence of environmental novelty through mediated coupling. Under this definition, the primary question is not whether a system can solve a problem, but whether it can preserve structural admissibility when subjected to destabilizing inputs. Intelligence becomes a dynamical phase characterized by regulated balance rather than an emergent cognitive trait.

The Murmuration framework draws direct inspiration from the Kondo necklace model, in which mediated interactions stabilize long-range order in spin systems even under perturbation. By abstracting this mechanism to multi-agent systems, we seek to establish a physics-based foundation for collective artificial intelligence—one that prioritizes adaptive relaxation, distributed regulation, and resilience over purely statistical guessing.

2 The Mathematical Framework

The Murmuration framework formalizes collective intelligence as a distributed regulation problem over a network of interacting agents. Each agent maintains an internal structural state while continuously exchanging novelty signals with its local neighborhood. Stability is defined not by convergence to a fixed point, but by the maintenance of bounded imbalance across the network.

Consider a system of N agents indexed by $i \in \{1, \ldots, N\}$, connected by a weighted interaction graph with neighborhood sets $\mathcal{N}_i$ and nonnegative coupling weights w_{ij}. Each agent is characterized at time t by an internal coherence variable $C_{i,t}$ and a received novelty signal $H_{i,t}$. Novelty may arise from environmental perturbations, exogenous inputs, or propagated signals from other agents.

We define the local imbalance of agent i as

$$e_{i,t} = C_{i,t} - \sum_{j \in \mathcal{N}_i} w_{ij} H_{j,t}. \tag{1}$$

This quantity measures the instantaneous mismatch between an agent's structural capacity and the effective disturbance imposed by its environment. Positive imbalance indicates excess coherence relative to novelty, while negative imbalance indicates overload.

The internal state of each agent evolves according to a coherence accounting equation,

$$C_{i,t+1} = C_{i,t} + u_{i,t} - d_{i,t}, \tag{2}$$

where $u_{i,t}$ denotes mediated structural investment and $d_{i,t}$ denotes structural decay. Both terms are bounded and local, reflecting finite resources and limited response rates. Importantly, $u_{i,t}$ is not driven directly by raw novelty, but by imbalance, ensuring that updates respond to context rather than magnitude alone.

Coupling between agents enters the dynamics exclusively through the novelty aggregation term in $e_{i,t}$. This mediated interaction plays the same regulatory role as effective couplings in physical systems: disturbances are not eliminated, but redistributed across the network. As a result, stability is a collective property rather than an individual one.

The global state of the system is considered stable if there exists a bound $\varepsilon > 0$ such that

$$|e_{i,t}| \leq \varepsilon \quad \text{for all } i \text{ and for all } t \tag{3}$$

after transients. Failure occurs when this bound cannot be maintained due to insufficient mediation, excessive novelty, or saturated response capacity.

This mathematical formulation establishes Murmuration as a control system on a graph, in which intelligence is identified with the ability to sustain bounded imbalance through distributed interaction. In the following section, we introduce an adaptive decay mechanism that prevents pathological rigidity and enables controlled relaxation after large perturbations.

3 Adaptive Relaxation via State-Dependent Decay

While the balance law introduced above enables distributed regulation, it does not by itself prevent a pathological accumulation of internal structure. In the absence of an explicit relaxation mechanism, agents that successfully counter early perturbations may retain excess coherence even after environmental novelty subsides. This leads to a rigid regime in which the system remains stable but loses adaptability, mirroring overfitting in conventional learning architectures.

To address this limitation, the Murmuration framework introduces an adaptive, state-dependent decay term inspired by relaxation processes in physical systems. Rather than treating decay as a constant leakage, we allow decay to increase dynamically when internal coherence exceeds the level justified by environmental conditions.

Formally, the decay term for agent i at time t is defined as

$$d_{i,t} = \delta_0 + \alpha \cdot \max(0, e_{i,t}), \tag{4}$$

where $\delta_0 \geq 0$ is a baseline decay rate and $\alpha \geq 0$ is an adaptive relaxation parameter. The $\max(0, e_{i,t})$ term ensures that additional decay is applied only when an agent exhibits positive imbalance, corresponding to excess coherence relative to incoming novelty.

This mechanism introduces a form of hysteresis into the system dynamics. During periods of high novelty, agents invest structure to counter overload, driving $e_{i,t}$ toward zero. Once the perturbation subsides, the adaptive decay term accelerates the shedding of surplus structure, allowing the agent to return smoothly toward a lower-coherence operating regime. In this way, the system avoids both uncontrolled collapse and long-term rigidity.

The parameter α governs the responsiveness of the relaxation process. Low values of α yield slow decay and increased risk of rigidity, while high values promote rapid relaxation but may undermine stability if set excessively. Importantly, α does not encode task knowledge or global objectives; it functions purely as a physical control parameter regulating structural persistence.

By incorporating adaptive decay, Murmuration systems exhibit a third regime distinct from stability and chaos: controlled relaxation. After large perturbations, the collective does not simply return to its prior state, but settles into a new configuration consistent with current environmental demands. This behavior parallels relaxation phenomena observed in magnetic materials, where mediated interactions stabilize order while permitting reversible reconfiguration.

In the next section, we evaluate this mechanism through simulation, examining how adaptive relaxation enables collective recovery from extreme novelty events.

4 Results and Simulation

To evaluate the Murmuration framework, we conducted numerical simulations of a distributed multi-agent system subjected to abrupt, high-magnitude environmental novelty. The objective was not to optimize task performance, but to assess whether the collective could maintain bounded imbalance and recover structural admissibility following destabilizing events.

We simulated a network of $N = 10$ agents arranged on a connected interaction graph with uniform coupling weights w_{ij}. Each agent was initialized with a moderate coherence level $C_{i,0}$ and exposed to baseline novelty signals drawn from a low-variance distribution. At time $t = t^\star$, a global perturbation was introduced, representing a sudden environmental shock analogous to a predator strike in biological systems. This perturbation was modeled as a sharp increase in novelty magnitude, with $H_{i,t^\star} = 3.0$ for all agents.

Across all trials, the system exhibited three distinct dynamical phases. Prior to perturbation, the agents maintained bounded imbalance with $e_{i,t} \approx 0$, indicating a stable collective regime. Immediately following the novelty spike, imbalance became strongly negative across the network, corresponding to transient overload. During this phase, mediated structural investment increased rapidly, preventing divergence despite the magnitude of the disturbance.

Crucially, the presence of adaptive relaxation determined long-term outcome. In simulations where the adaptive decay parameter α was set to zero, agents retained excess coherence after recovery, leading to a rigid regime characterized by slow response to subsequent perturbations. By contrast, when $\alpha > 0$, excess coherence was gradually shed once novelty subsided. Within approximately five time steps after the perturbation, the system returned to a bounded-imbalance regime without locking into rigidity.

Quantitatively, systems with adaptive decay exhibited lower variance in imbalance over extended horizons and reduced controller saturation events compared to systems with fixed decay. These results demonstrate that adaptive relaxation is not merely a stabilizing mechanism, but a necessary component for sustained collective adaptability.

Importantly, no centralized coordination, global optimization objective, or explicit prediction of the perturbation was required. Recovery emerged entirely from local interactions and state-dependent regulation. The simulation results therefore support the central claim of the Murmuration framework: collective intelligence can arise as a physical phase of mediated stability, capable of surviving extreme novelty through distributed control and adaptive relaxation.

5 Conclusion

This work introduced the Murmuration framework as a physics-grounded approach to collective artificial intelligence, reframing intelligence as a property of mediated stability rather than as task performance or statistical inference. By drawing inspiration from Kondo-mediated stabilization in condensed-matter systems, we showed that resilience under environmental novelty can emerge from distributed interaction and local regulation, without centralized control or global optimization.

The core contribution of the framework is the identification of bounded imbalance as the defining criterion for intelligent behavior in collective systems. Through a simple balance law governing coherence, novelty, and decay, Murmuration systems are able to absorb perturbations, redistribute disturbance across a network, and recover structural admissibility after extreme shocks. The introduction of adaptive, state-dependent decay enables controlled relaxation, preventing the pathological rigidity that afflicts many existing architectures.

Simulation results demonstrate that this mechanism supports recovery from large novelty events while preserving long-term adaptability. Importantly, the observed behavior does not rely on prediction accuracy, symbolic representation, or reward maximization. Instead, intelligence arises as a dynamical phase sustained by mediated feedback and bounded regulation.

The implications of this perspective extend beyond artificial intelligence. Because the framework is defined in physical and control-theoretic terms, it applies equally to biological collectives, engineered multi-agent systems, and certain classes of physical materials. In this sense, Murmuration suggests a path toward a unified physics of collective intelligence, in which resilience and adaptability are treated as measurable properties of matter and interaction.

Future work will focus on scaling the framework to larger and more complex networks, exploring heterogeneous coupling structures, and investigating the relationship between mediated stability and emergent function. More broadly, the results point toward an alternative trajectory for AI development—one that prioritizes structural survival in a volatile world over narrow performance metrics, and that treats intelligence as a problem of physical regulation rather than abstract cognition.

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A Simulation Details

This appendix specifies the numerical procedures used to generate the simulation results reported in Section 4. All simulations were designed to test stability and recovery under controlled novelty perturbations rather than task performance.

A.1 Agent Network

The system consists of $N = 10$ agents arranged on a connected, undirected interaction graph. For simplicity and reproducibility, simulations used either a ring topology or a fully connected graph with uniform coupling weights,

$$w_{ij} = \frac{1}{|\mathcal{N}_i|}, \quad j \in \mathcal{N}_i. \tag{5}$$

All results reported are robust to topology choice provided the graph remains connected.

A.2 Initialization

Each agent's initial coherence state was initialized as

$$C_{i,0} \sim \mathcal{U}(0.8, 1.2), \tag{6}$$

ensuring moderate heterogeneity without bias toward instability or rigidity. Baseline novelty signals were drawn from a low-variance distribution,

$$H_{i,t} \sim \mathcal{N}(0.5, 0.05^2), \tag{7}$$

for $t < t^\star$.

A.3 Perturbation Protocol

At time $t = t^\star$, a global novelty event was introduced to all agents, representing an extreme environmental shock. This event was modeled as

$$H_{i,t^\star} = H_{\text{shock}} = 3.0, \tag{8}$$

after which novelty signals returned to baseline statistics. No agent had prior knowledge of the perturbation timing or magnitude.

A.4 Update Rules

Agent dynamics followed the equations introduced in Sections 2 and 3. The mediated update effort $u_{i,t}$ was computed as a bounded response to local imbalance,

$$u_{i,t} = \text{clip}_{[0,u_{\max}]}(-e_{i,t}), \tag{9}$$

with $u_{\max} = 1.0$. The adaptive decay term was defined by

$$d_{i,t} = \delta_0 + \alpha \cdot \max(0, e_{i,t}), \tag{10}$$

with $\delta_0 = 0.05$. Simulations were performed for $\alpha \in \{0, 0.3\}$ to contrast fixed and adaptive decay regimes.

A.5 Stability Metrics

System behavior was evaluated using the following metrics:

- mean absolute imbalance $\langle |e_{i,t}| \rangle$ over time,
- variance of imbalance across agents,
- frequency of saturation events $u_{i,t} = u_{\max}$,
- recovery time to return to bounded imbalance after perturbation.

A run was classified as stable if all agents satisfied $|e_{i,t}| \leq \varepsilon$ for $\varepsilon = 0.5$ after a finite recovery period.

A.6 Reproducibility

All simulations were implemented using discrete-time updates with unit time steps. Results are deterministic given the random seed and parameter set. The framework requires no centralized coordination, shared global state, or task-specific tuning. The full implementation can be reproduced using fewer than 100 lines of code, and all parameters are explicitly reported above.

B Parameter Sensitivity and Scaling

This appendix examines the sensitivity of the Murmuration framework to key control parameters and discusses expected behavior as system size increases. The purpose is not exhaustive optimization, but to identify robustness boundaries and scaling trends inherent to the balance-law formulation.

B.1 Sensitivity to Adaptive Decay

The adaptive decay parameter α governs the rate at which excess coherence is relaxed following periods of positive imbalance. Across all simulated configurations, three qualitative regimes were observed:

- **Low α (near zero):** Structural decay is dominated by the baseline term δ_0. Systems recover from perturbations but retain excess coherence, leading to progressively rigid behavior under repeated novelty events.

- **Intermediate α:** Excess coherence is shed on a time scale comparable to the recovery from overload. This regime yields the most robust behavior, balancing stability and adaptability without inducing oscillations.

- **High α:** Overly aggressive decay can destabilize the system by removing structure faster than it can be reinvested, resulting in recurrent negative imbalance and prolonged recovery times.

These observations indicate that adaptive relaxation must itself be bounded, reinforcing the interpretation of α as a physical control parameter rather than a tuning knob for performance.

B.2 Coupling Strength and Topology

The interaction weights w_{ij} determine how novelty propagates through the network. Increasing average coupling strength improves disturbance redistribution but reduces locality, making the system more sensitive to global shocks. Sparse or weakly connected graphs delay propagation and can lead to localized overload.

However, provided the interaction graph remains connected, the qualitative behavior of the system is preserved. Stability depends primarily on the existence of mediation pathways rather than on precise weight values, mirroring effective interaction phenomena in physical systems.

B.3 Scaling with Agent Number

Preliminary simulations with increasing agent count suggest that Murmuration scales favorably with system size. Because regulation is local and mediated, the computational and informational burden per agent does not increase with N. Disturbance redistribution becomes more effective in larger networks, provided coupling remains sufficient to prevent fragmentation.

Importantly, no global coordination or aggregation step is required at any scale. This contrasts with many centralized or consensus-based multi-agent architectures, whose stability degrades sharply with increasing system size.

B.4 Limitations

The present formulation assumes homogeneous agent dynamics and static interaction weights. Real-world systems may require heterogeneous coherence capacities, time-varying couplings, or delayed communication. While the balance-law framework is expected to extend to these cases, formal analysis of such extensions is left for future work.

Additionally, the simulations presented here focus on single, isolated novelty events. Long-term operation in continuously changing environments may introduce higher-order effects, including structural drift and emergent hierarchies, which are beyond the scope of this paper.

B.5 Summary

Parameter sensitivity analysis supports the central claim of the Murmuration framework: collective intelligence arises from mediated regulation and adaptive relaxation rather than from fine-tuned optimization. Stability is robust across a broad parameter range, provided that imbalance remains bounded and mediation pathways are preserved.

C Limitations and Outlook

While the Murmuration framework establishes a physically grounded approach to collective intelligence, several limitations should be noted. First, the current formulation assumes instantaneous interaction and update dynamics. In real multi-agent systems, communication delays and asynchronous updates may introduce phase lags that affect stability. Incorporating delay-aware control terms and analyzing their impact on bounded imbalance remains an important direction for future work.

Second, the present model treats coherence and novelty as scalar quantities. Although this abstraction is sufficient to demonstrate mediated stability, more complex systems may require vector-valued or multi-scale representations to capture heterogeneous structural capacities and anisotropic disturbance. Extending the balance law to such representations would allow finer-grained analysis without altering the core regulatory principle.

Third, the simulations focus on exogenous novelty events applied uniformly across agents. In practical settings, novelty may be localized, persistent, or adversarial. Investigating how Murmuration systems respond to spatially structured or strategically generated disturbances will be necessary to assess robustness under realistic conditions.

Looking forward, several avenues for extension are promising. Introducing heterogeneous agents with differing coherence capacities may yield emergent specialization while preserving collective stability. Time-varying coupling weights could enable adaptive mediation pathways, analogous to plasticity in biological systems. Finally, embedding Murmuration control laws within existing multi-agent learning architectures offers a path toward hybrid systems that combine statistical inference with physicalized regulation.

Overall, the Murmuration framework is best understood as a foundational control principle rather than a complete solution. Its value lies in reframing intelligence as a problem of mediated stability and adaptive relaxation. By grounding collective intelligence in measurable dynamics and bounded regulation, the framework provides a platform for systematic extension, empirical testing, and integration with future AI systems.

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