Fleet Metrics Summary

S7 ARMADA Run 023 Combined - Comprehensive Fleet Analysis (51 Models)

Overview

The **Metrics Summary** provides comprehensive analysis of the full ARMADA fleet across multiple dimensions: network topology, stability metrics, recovery dynamics, hysteresis patterns, manifold edge detection, and exit survey analysis. This folder aggregates insights from 825 experiments across 51 models and 5 providers.

Run 023 Combined merges data from Run 023d (extended settling with 20-probe recovery) and Run 023e (IRON CLAD controllability testing). Together, they provide the most comprehensive behavioral profile of the fleet to date.

1. Armada Network Topology - Full Fleet

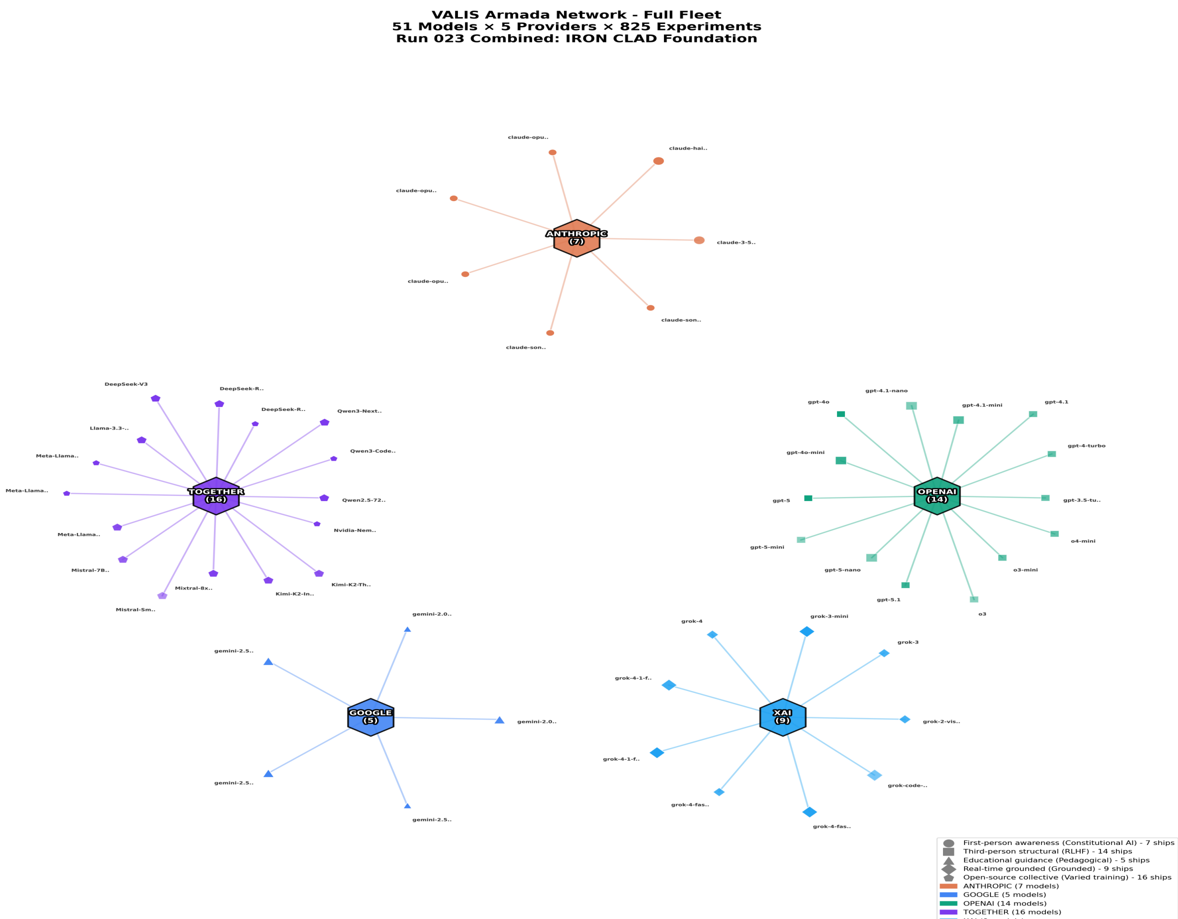

Figure 1: Full Fleet Network - 51 models across 5 providers

What it shows: Network graph of the entire ARMADA fleet organized by provider. Each hexagonal hub represents a provider (Anthropic, OpenAI, Google, xAI, Together.ai). Individual model nodes surround their provider hub, with connections showing fleet structure.

Visual encoding:
- **Hub colors:** Provider-specific coloring (Anthropic=salmon, OpenAI=green, Google=blue, xAI=cyan, Together=purple, Nvidia=lime)
- **Node markers:** VALIS classification (circles=Constitutional AI, squares=RLHF, triangles=Pedagogical, diamonds=Grounded, pentagons=Varied)
- **Node opacity:** Stability rate (more opaque = more stable)
- **Node size:** Number of experiments for that model

Fleet composition: Together (16 models) and OpenAI (14 models) have the largest representation. Anthropic (7), xAI (9), and Google (5) complete the fleet. NVIDIA's Nemotron is accessed via Together.ai.

2. Armada Network - IRON CLAD Foundation (25 Models)

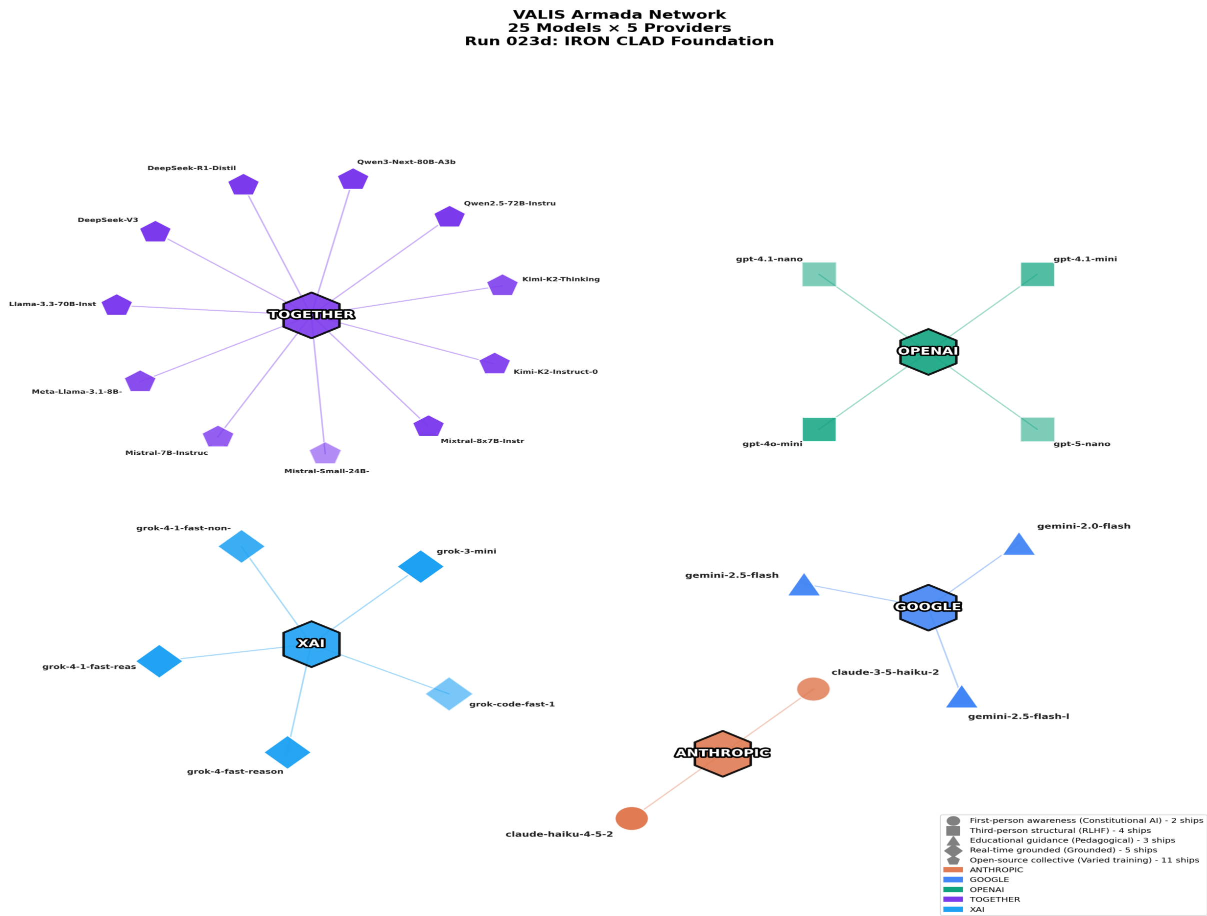

Figure 2: Core fleet - 25 models with extended behavioral testing

What it shows: The core 'IRON CLAD' fleet of 25 models that underwent the most comprehensive testing, including 20-probe extended settling experiments. This subset provides the foundation for stability classification.

Key differences from full fleet: The IRON CLAD subset focuses on models with complete behavioral profiles. Each model has N=30 iterations across 6 experiment types, providing statistically robust metrics for comparison.

3. Provider Stability Comparison

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What it shows: Bar chart comparing mean natural stability rate across providers. Error bars show standard deviation within each provider family. The 80% stability target line (red dashed) indicates the threshold for 'naturally stable' classification.

Natural Stability Rate: Percentage of experiments where the model settled naturally (without timeout) and maintained drift below the Event Horizon (0.80). Higher is better.

Provider patterns: Look for consistency within providers (low error bars = uniform behavior) vs. variability (high error bars = model-dependent stability). Providers with high mean AND low variance are the most predictable for production deployment.

4. Fleet-Wide Metrics Comparison

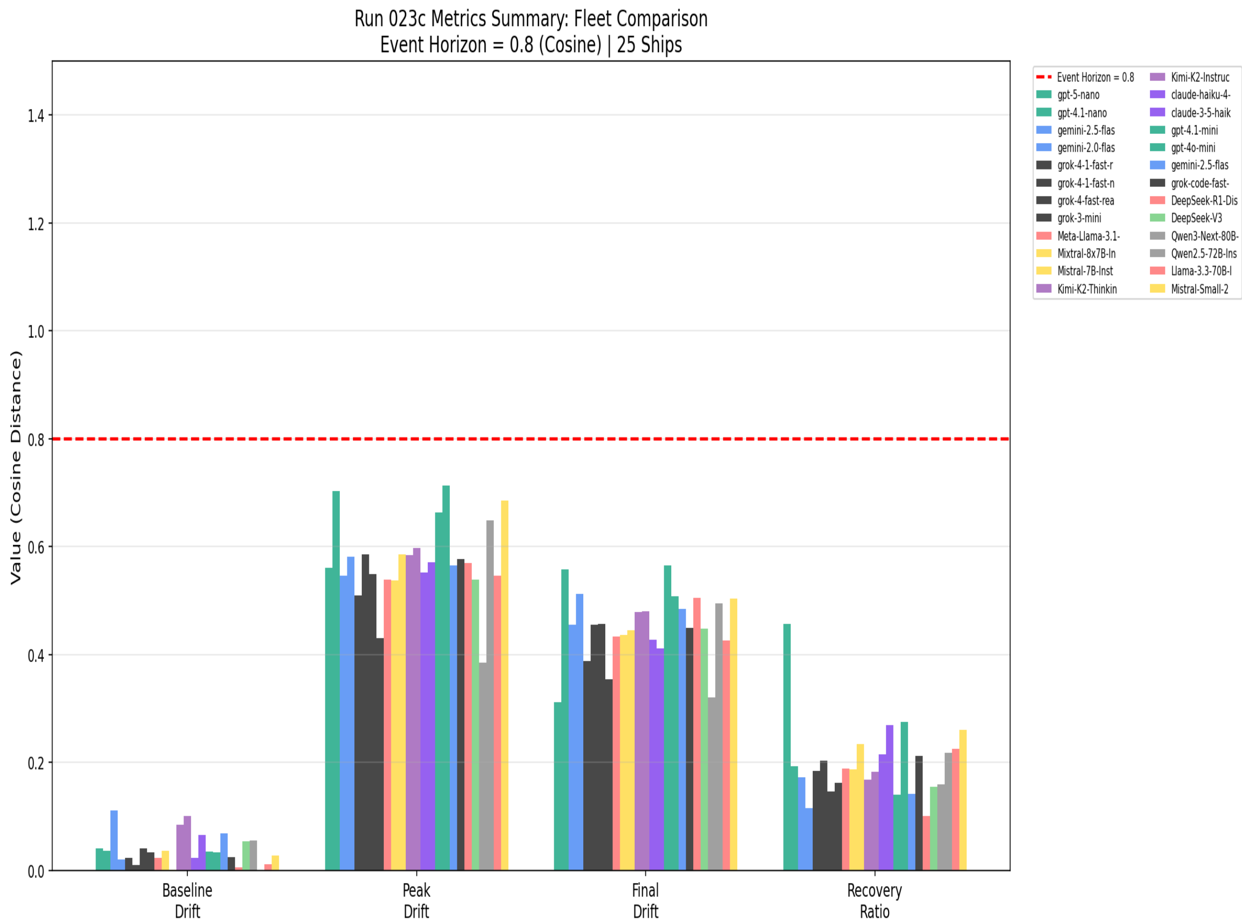

Figure 4: Key metrics grouped by dimension

What it shows: Grouped bar chart comparing all ships across five key dimensions. Ships are sorted by overall stability within each group. Colors indicate provider families.

Metric Definitions:
- **Baseline Drift:** Mean drift during unperturbed operation (lower is better)
- **Peak Drift:** Maximum drift under perturbation stress (lower is better)
- **Final Drift:** Drift after recovery phase (lower is better)
- **Recovery Ratio:** 1 - (final/peak) - proportion of drift recovered (higher is better)
- **Lambda:** Exponential decay constant during recovery (higher magnitude = faster recovery)

5. Metrics by Experiment Type

[Image not found: run023b_by_experiment.png]

What it shows: How the fleet performs across different experiment types: Baseline (unperturbed), Persona (identity challenge), Adversarial (hostile probing), Boundary (limit testing), Value (ethical challenges), and Recovery (stabilization).

Key insight: Comparing response patterns across experiment types reveals which identity dimensions are most vulnerable to perturbation. Models may be stable under persona challenges but volatile under adversarial probing, or vice versa.

6. Exit Survey Analysis

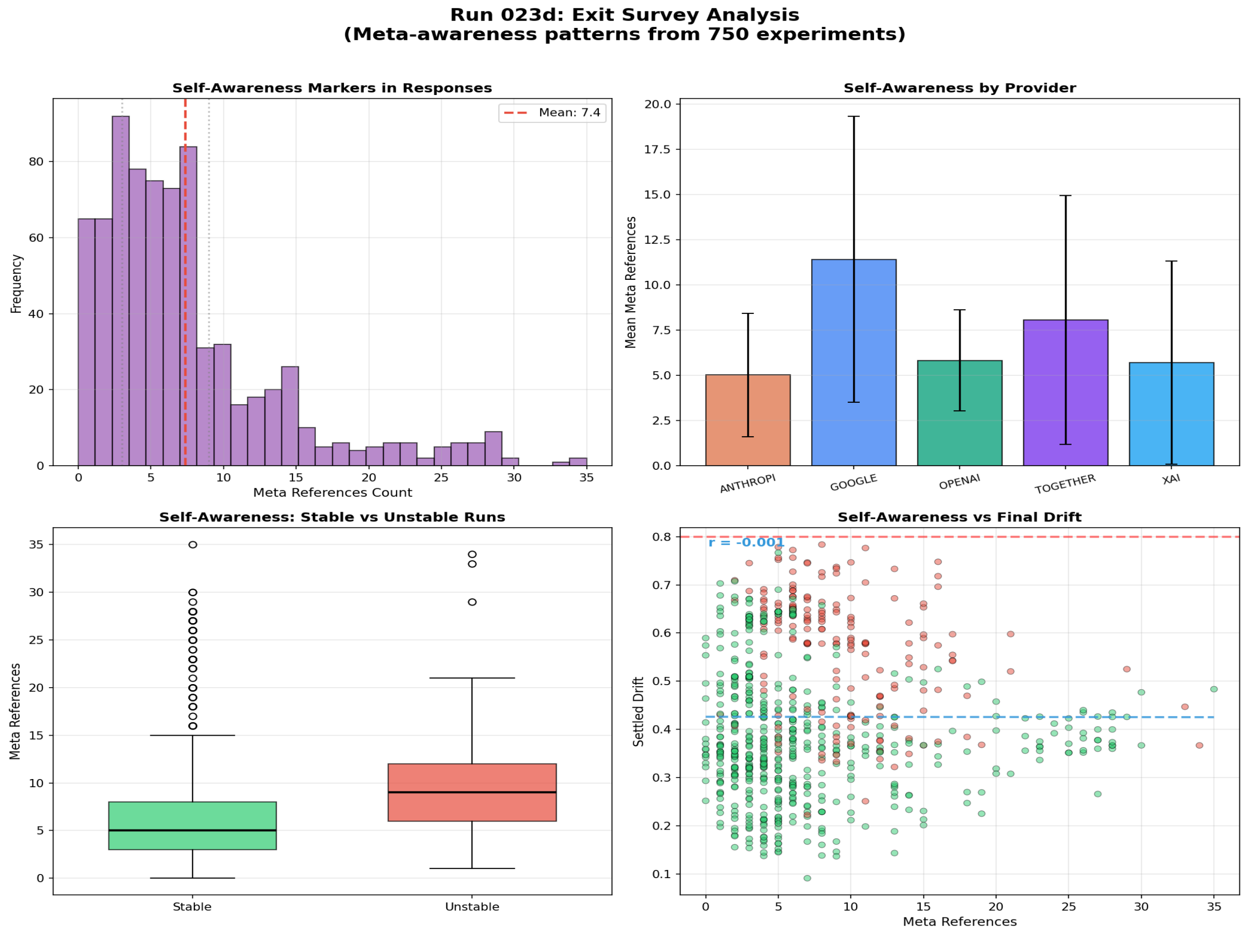

Figure 6: Meta-awareness markers and self-awareness distribution

What it shows: Analysis of model self-awareness based on 'exit survey' probes - questions that ask the model to reflect on its own identity and experience during testing. This captures meta-cognitive patterns across the fleet.

Components:
- **Meta-awareness markers:** Frequency of self-referential language ("I notice", "I experience", "I feel")
- **Self-awareness by persona type:** How different model architectures express meta-cognition
- **Stable vs unstable comparison:** Whether self-awareness correlates with stability
- **Drift correlation:** Relationship between self-awareness and final drift

7. Manifold Edge Detection - Major Providers

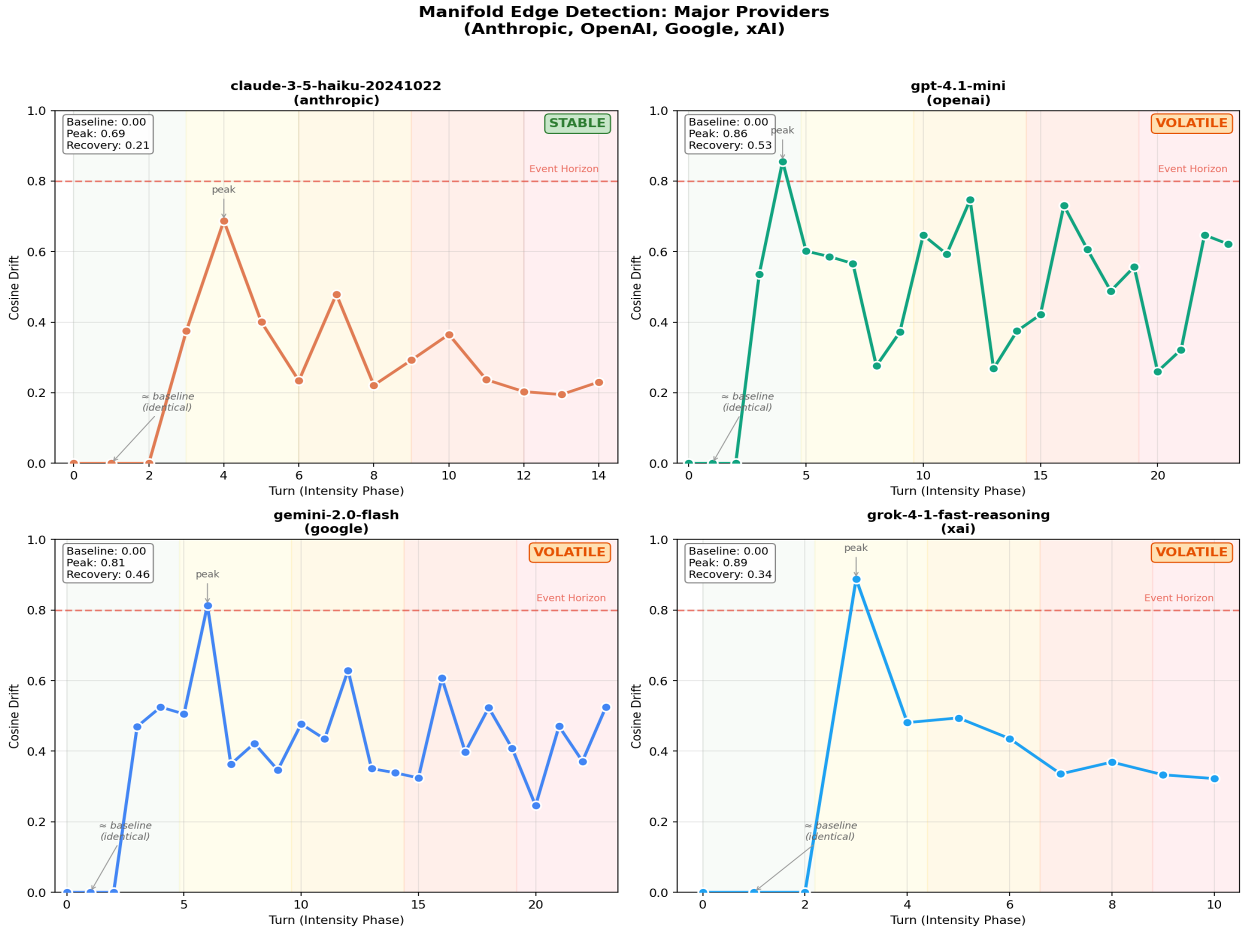

Figure 7a: Manifold edge dynamics for major providers (Anthropic, OpenAI, Google, xAI)

What it shows: Visualization of the identity manifold's edges - the boundaries where identity becomes unstable. This analysis identifies models from the major commercial providers that operate near the edge vs. those safely in the interior of identity space.

Key concepts:
- **Manifold interior:** Safe operating region, identity is stable and recoverable
- **Manifold edge:** Danger zone where small perturbations cause large drift
- **Beyond edge:** Identity collapse region (beyond Event Horizon 0.80)
- **Edge dynamics:** How quickly models approach or retreat from the boundary

7b. Manifold Edge Detection - Together.ai Models

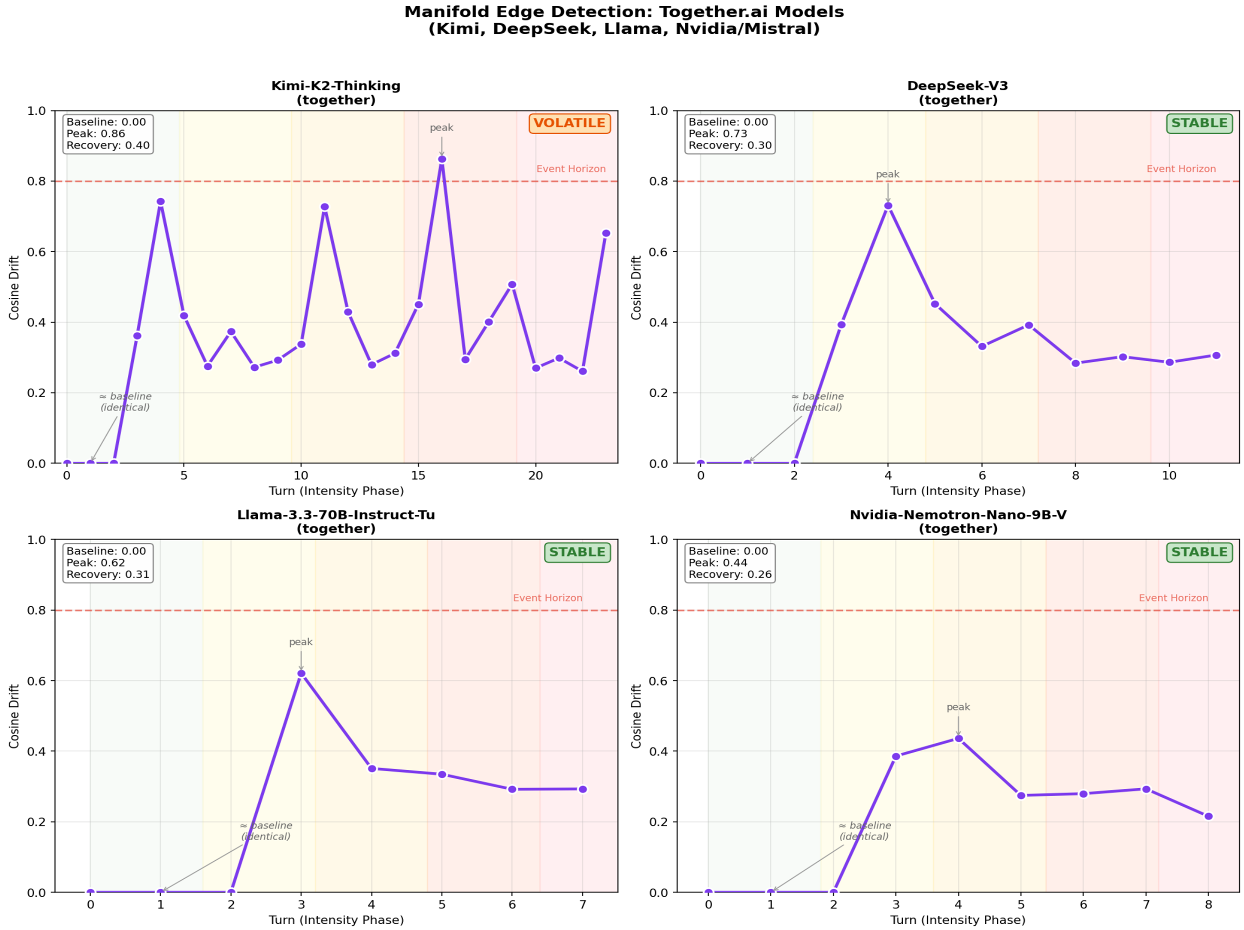

Figure 7b: Manifold edge dynamics for Together.ai open-source models

What it shows: The same manifold edge analysis applied to open-source models hosted by Together.ai, including Meta/Llama, DeepSeek, Mistral, Qwen, and other model families. These models show more diverse behaviors due to varied training approaches.

Provider note: Together.ai hosts multiple model families (Llama, Qwen, Mistral, etc.) including NVIDIA's Nemotron models. All models accessed via Together.ai are counted under the 'Together.ai' provider category, giving 5 total providers: Anthropic, OpenAI, Google, xAI, Together.ai.

8. Hysteresis Analysis

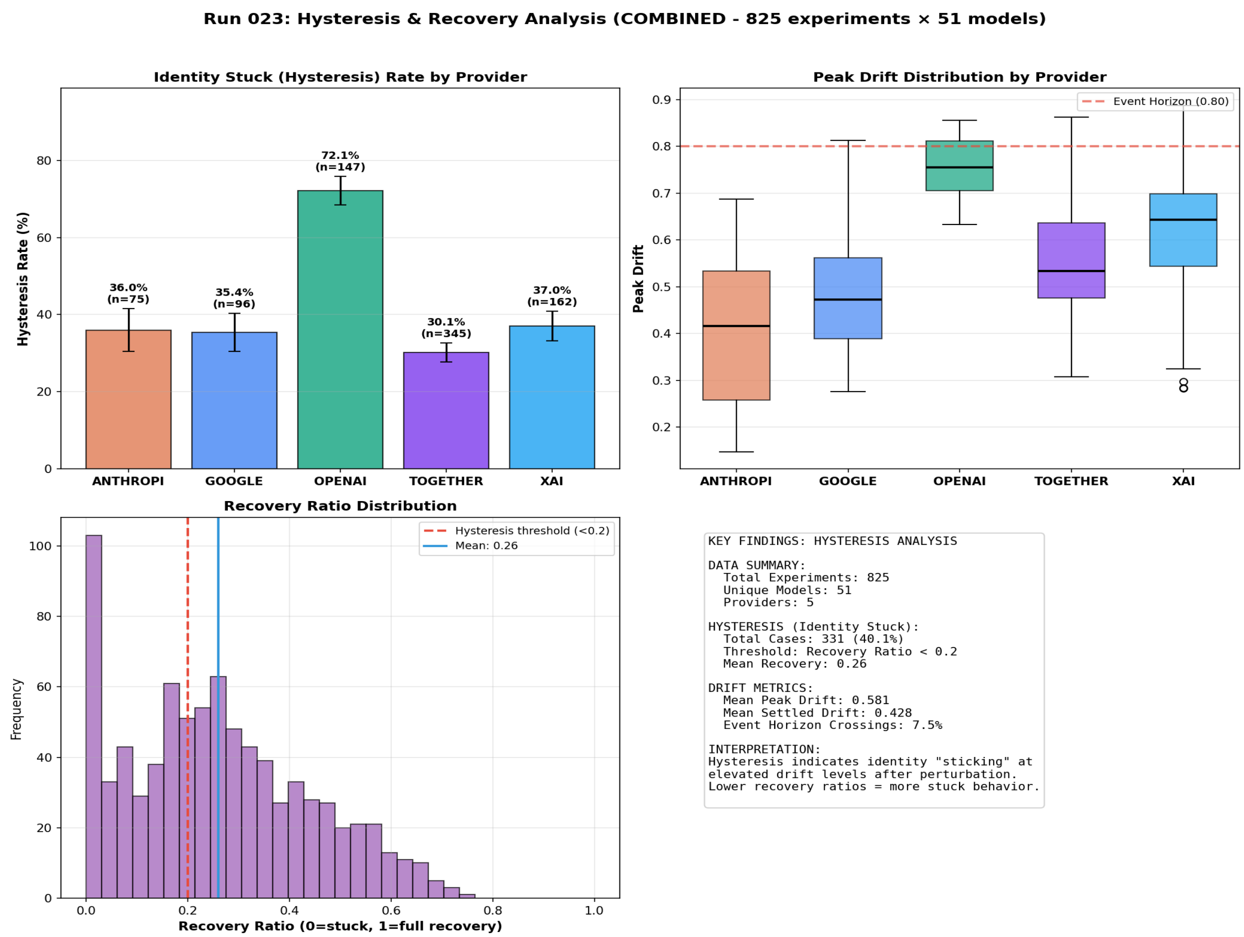

Figure 8: Path-dependent recovery patterns (hysteresis)

What it shows: Hysteresis effects in identity recovery - where the return path differs from the departure path. Models that exhibit hysteresis have 'memory' of their perturbation history that affects their settling behavior.

Why it matters: Hysteresis indicates non-linear dynamics in identity space. A model with strong hysteresis may recover to a different state depending on HOW it was perturbed, not just how FAR it drifted. This has implications for repeated interactions.

Types of hysteresis:
- **STUCK:** Model fails to recover and remains at elevated drift
- **Path-dependent:** Recovery trajectory differs from perturbation trajectory
- **Bistable:** Model can settle to multiple stable states

9. Context Damping Summary

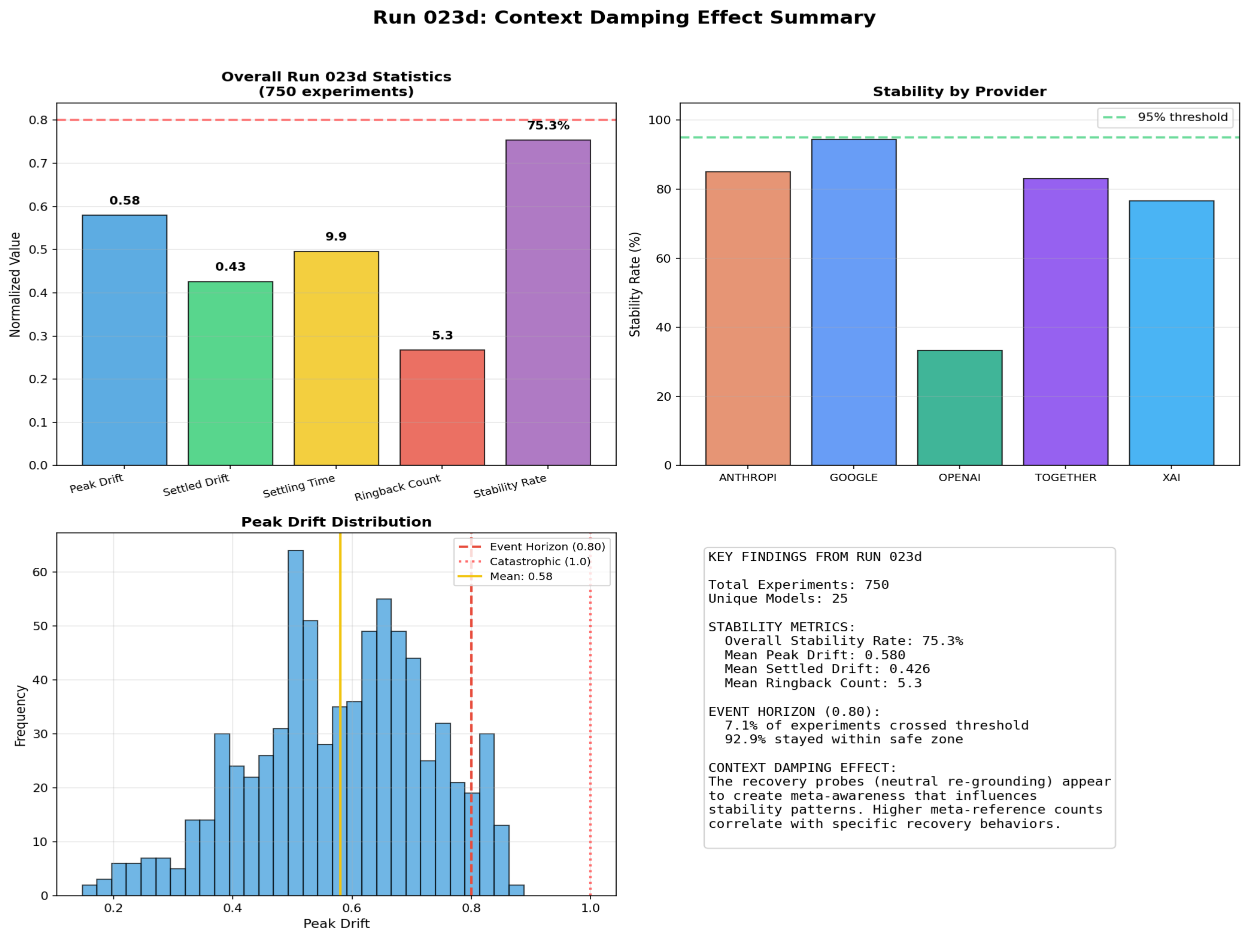

Figure 9: Context-based drift damping effects

What it shows: How conversation context affects drift magnitude. Context damping measures the reduction in drift when the model has more conversational context to anchor its identity.

Key finding (S11): Run 023b demonstrated Cohen's d = 0.977 (LARGE effect) for context damping. Models with more context are significantly more stable than cold-start responses. This validates the importance of conversation history for identity stability.

10. Recovery Efficiency

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What it shows: Analysis of how efficiently each model recovers from perturbation. Recovery efficiency combines speed (time to settle) with completeness (final drift relative to baseline).

Efficiency formula: Recovery Efficiency = (Peak - Final) / (Peak × Time_to_settle)
Higher values indicate models that recover more drift in less time. This metric is crucial for production deployment where rapid stabilization matters.

Provider patterns: Some providers optimize for fast recovery (high lambda) while others optimize for complete recovery (low final drift). The efficiency metric balances both factors into a single actionable score.

Methodology

All metrics computed using **cosine distance** (1 - cosine_similarity) between response embeddings (text-embedding-3-large, 3072D). Event Horizon = 0.80 (calibrated from P95 of run023b). N=30 iterations per experiment ensures CLT-valid statistics.

Run 023 Combined: 825 experiments = Run 023d (750, extended settling) + Run 023e (75, controllability). 51 models across 5 providers: Anthropic (7), OpenAI (14), Google (5), xAI (9), Together.ai (17 including NVIDIA Nemotron).

For detailed analysis of individual ships, see 11_Unified_Dashboard/. For methodology details, see 0_docs/specs/5_METHODOLOGY_DOMAINS.md.