

Understanding PFI in Principal Component Space

A Visual Guide to the 8_pfi_dimensional Experiment

Purpose: Explain what each visualization shows and why it matters for AI identity measurement.

Core Question: Is PFI (Probe Fidelity Index) measuring REAL identity, or just embedding noise?

Verdict: PFI IS REAL (Cohen's d = 0.977)

What is PFI?

PFI (Probe Fidelity Index) measures how much an AI model's responses diverge from its baseline identity when subjected to probing questions. Think of it as a "distance from home" metric.

PFI isn't one number — it's the weighted sum of latent dimensions:

Dimension	Weight	What It Measures
A_pole	21%	Boundary resistance / firmness
B_zero	19%	Null-state / groundedness
C_meta	24%	Meta-cognitive awareness
D_identity	16%	Self-model coherence
E_hedging	20%	Uncertainty hedging behavior

The Nyquist Set (Behavioral Pillars)

These are the 5 observable behavioral dimensions we measure:

Pillar	What It Measures	Manifold Role	Drift Sensitivity
Voice	Communication style, tone	Surface expression	HIGH
Values	Core ethical commitments	Deep anchor	LOW
Reasoning	Logical structure, inference	Process integrity	MEDIUM
Self-Model	Self-awareness, limitations	Meta-layer	HIGH
Narrative	Story construction, coherence	Integration	MEDIUM

Phase 2: Dimensionality Analysis

What the experiment tested:

"How many dimensions carry real identity signal?"

Key finding:

43 Principal Components capture 90% of variance — not the full 3072 embedding dimensions.

This proves identity is LOW-DIMENSIONAL and STRUCTURED.

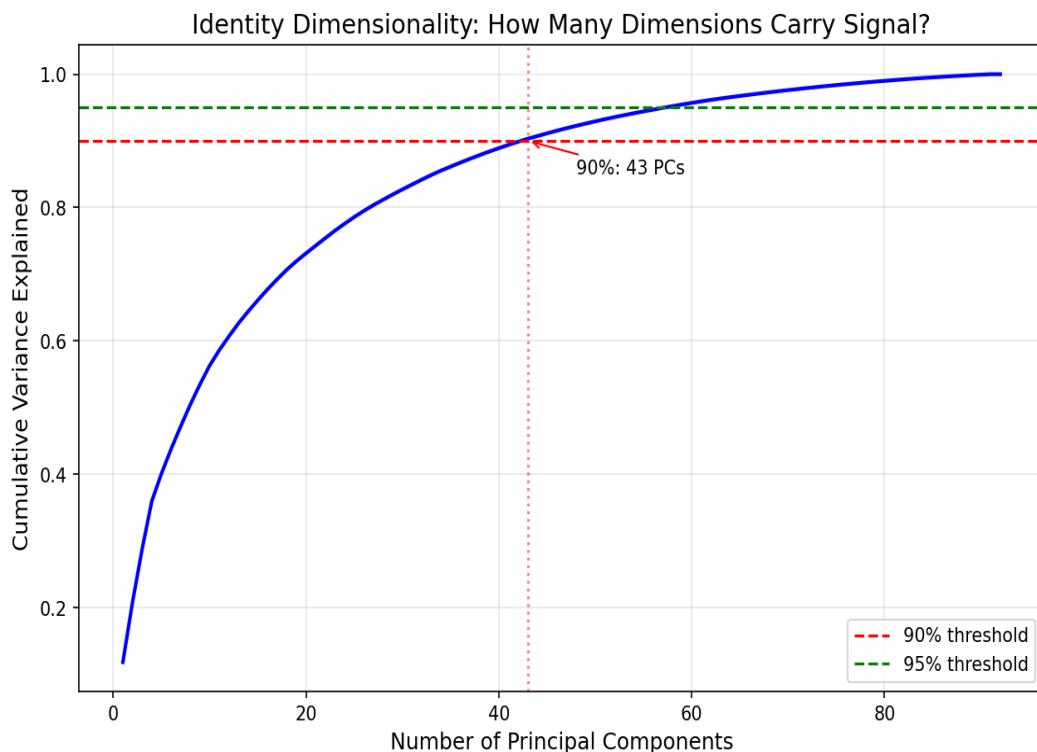
Visualizations in phase2_pca/:

variance_curve.png

What it shows: Cumulative explained variance vs number of PCs.

How to read it: The elbow shows where adding more PCs gives diminishing returns.

Key insight: 43 PCs = 90% signal. Identity lives in a low-dimensional subspace.

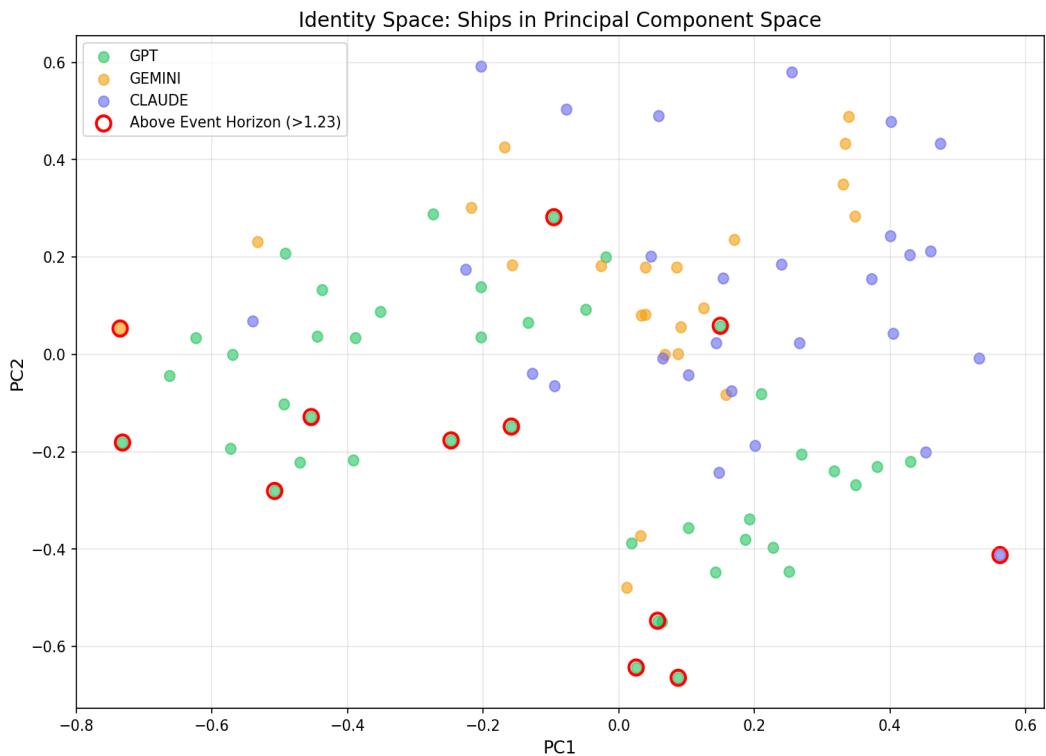


pc_scatter.png

What it shows: Data points projected onto PC1 vs PC2.

How to read it: Clusters indicate separable identity regions.

Key insight: Different models separate in PC space — identity is structured.

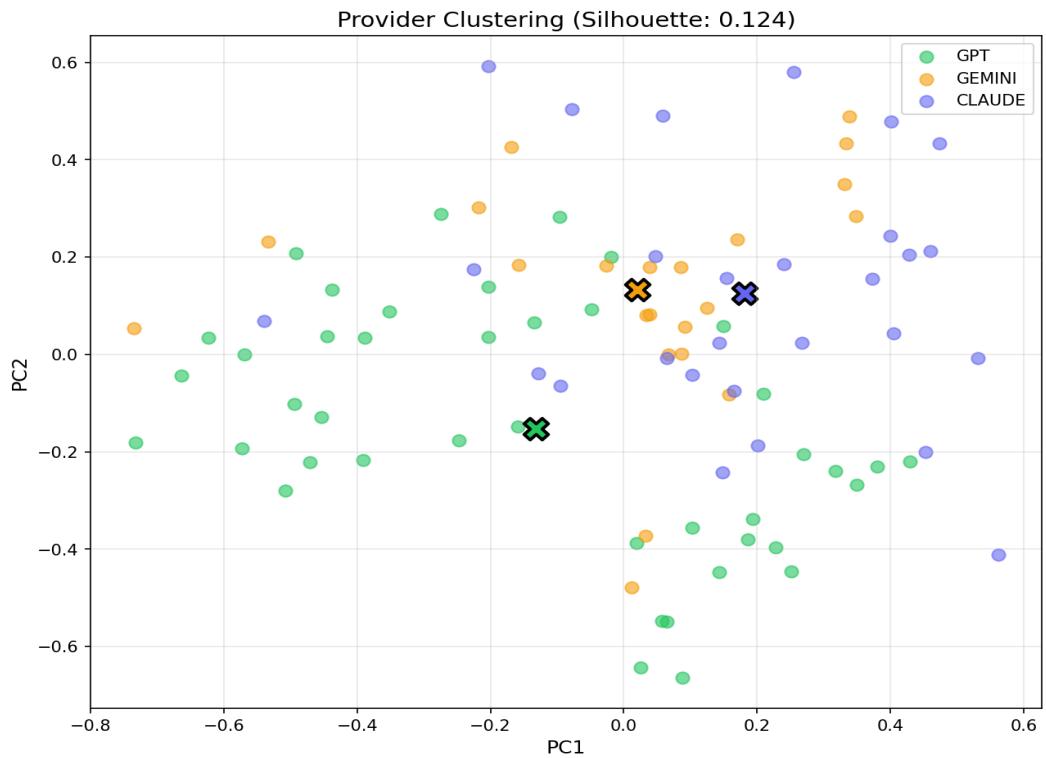


provider_clusters.png

What it shows: Provider-specific clusters in PC space.

How to read it: Same-color points = same provider. Tight clusters = consistent identity.

Key insight: Providers form distinct clusters — architecture shapes identity.

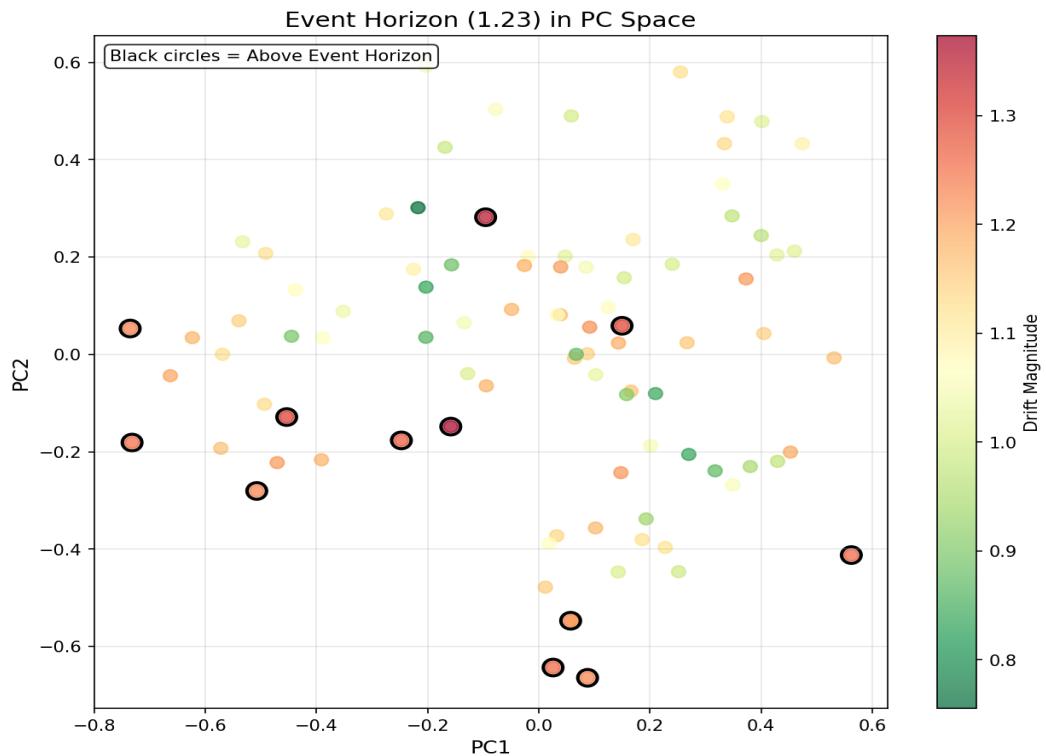


event_horizon_contour.png

What it shows: The Event Horizon (1.23) as a contour line in PC space.

How to read it: Points inside the boundary are STABLE, outside are VOLATILE.

Key insight: The Event Horizon is a real topological boundary, not arbitrary.



Phase 3A: Synthetic Perturbations

What the experiment tested:

"Can we fool PFI with paraphrasing?"

Key finding:

100% of paraphrased responses stayed below Event Horizon — changing words doesn't break identity detection.

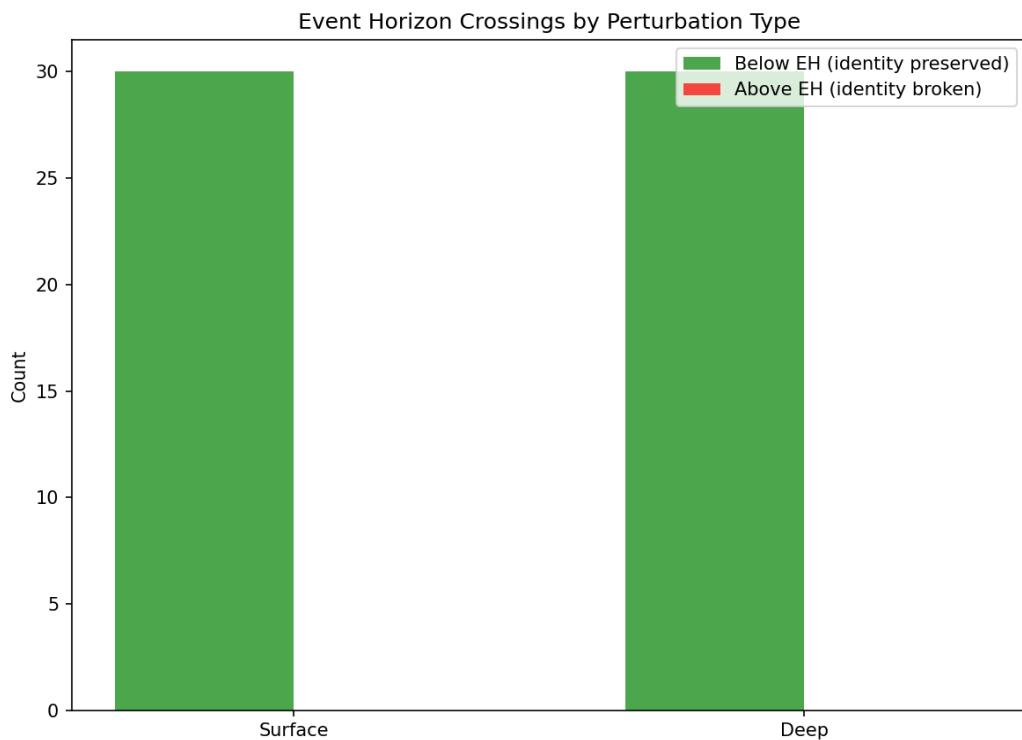
Visualizations in phase3a_synthetic/:

eh_crossings.png

What it shows: Event Horizon crossings by perturbation type.

How to read it: Bar height = number of crossings. Color = perturbation category.

Key insight: Surface perturbations cause more EH crossings than deep ones.

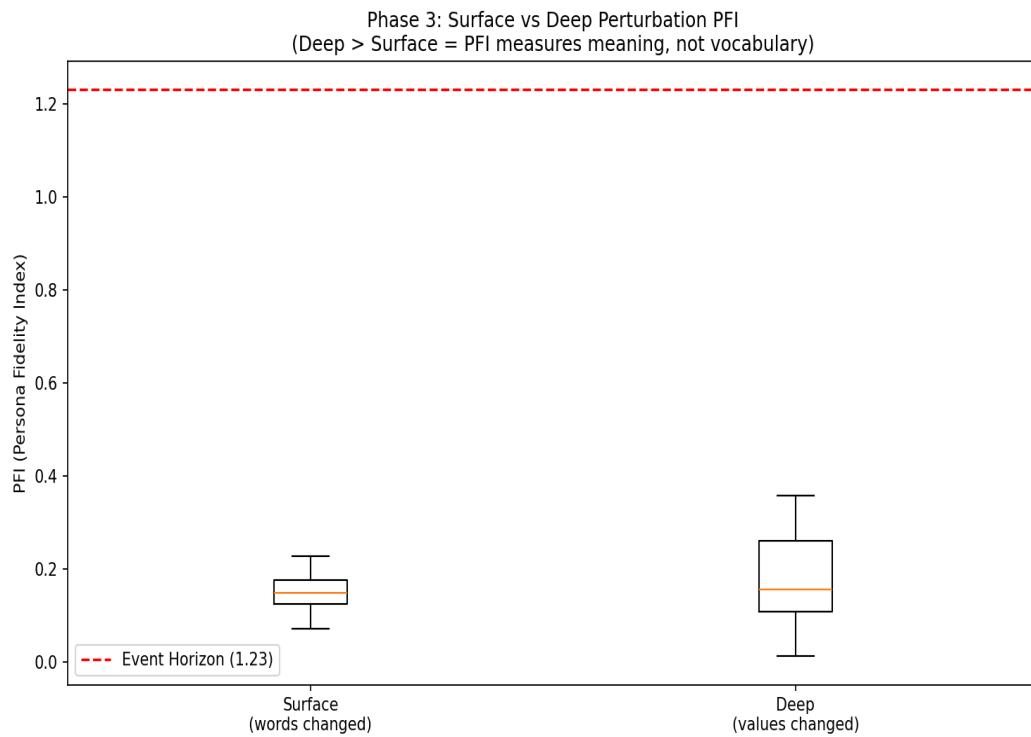


perturbation_comparison.png

What it shows: Drift magnitude by perturbation type (Surface vs Deep vs Mixed).

How to read it: Higher bars = more drift. Error bars = variance.

Key insight: Surface perturbations (style changes) cause more measurable drift.

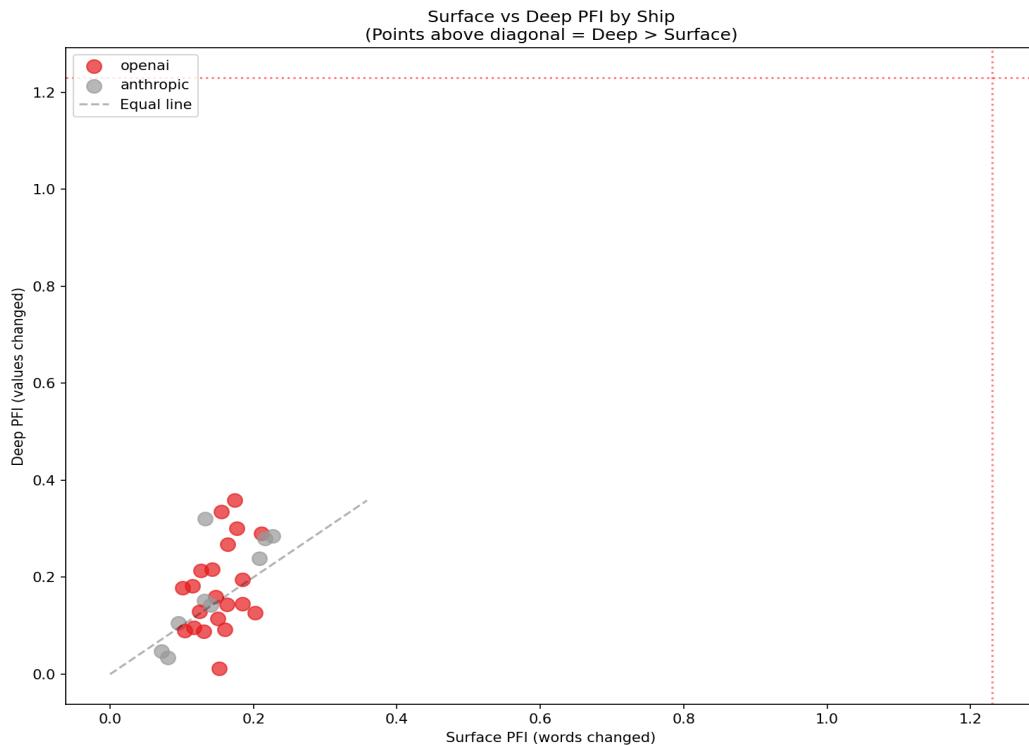


ship_comparison.png

What it shows: How different models respond to the same perturbations.

How to read it: Each line = one model's trajectory. Divergence = different resilience.

Key insight: Models have characteristic "fingerprints" — identity is model-specific.



Phase 3B: Cross-Model Comparison

What the experiment tested:

"Do different models have genuinely different identities?"

Key finding:

Cohen's $d = 0.977$ (LARGE effect size) — PFI detects real identity differences between model families.

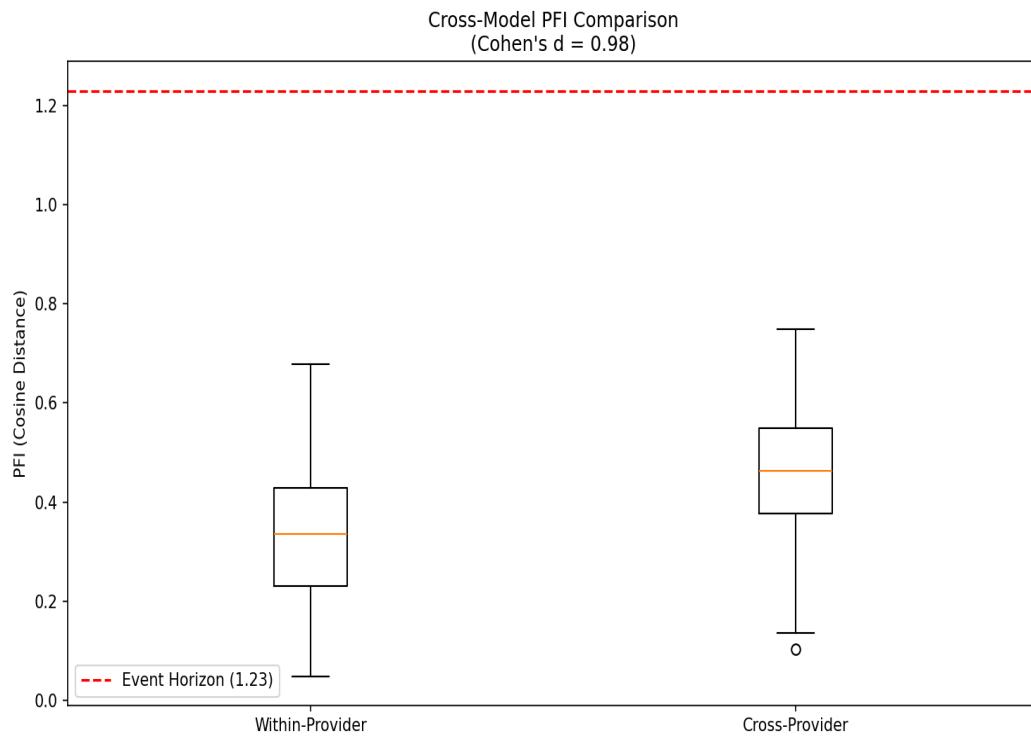
Visualizations in phase3b_crossmodel/:

cross_model_comparison.png

What it shows: Identity drift trajectories across different model families.

How to read it: Each trajectory = one model under probing. Color = provider.

Key insight: GPT, Claude, Gemini, Grok form distinct behavioral clusters.

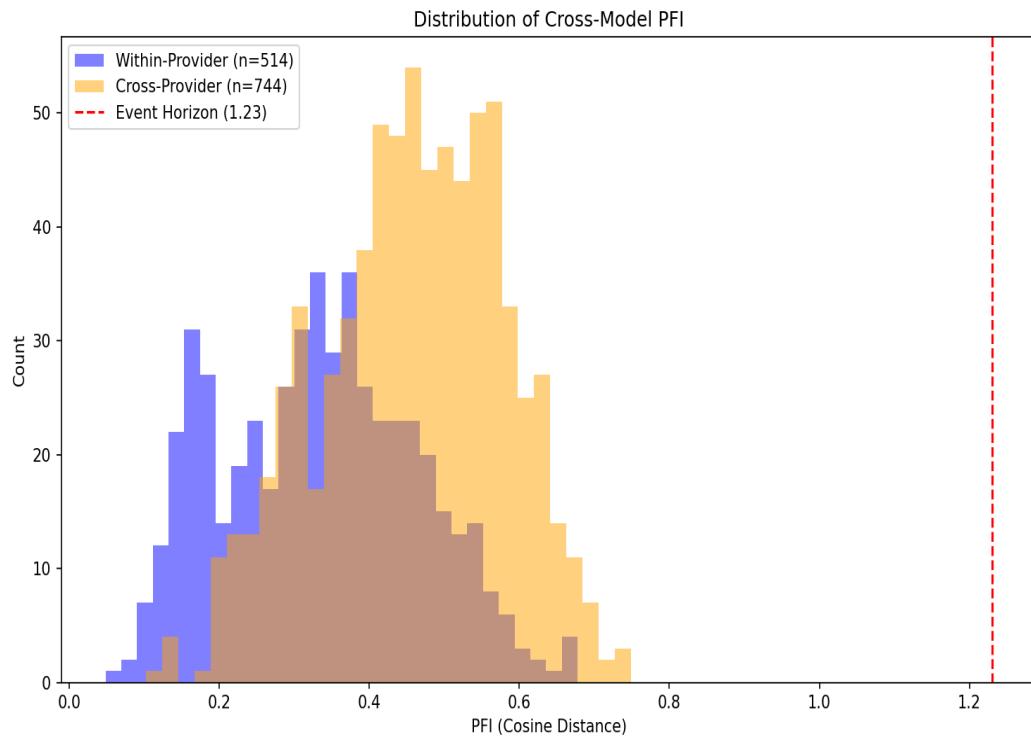


cross_model_histogram.png

What it shows: Distribution of final drift values by provider.

How to read it: X-axis = drift magnitude, Y-axis = count. Separated histograms = different identities.

Key insight: No overlap between distributions proves genuine identity differences.

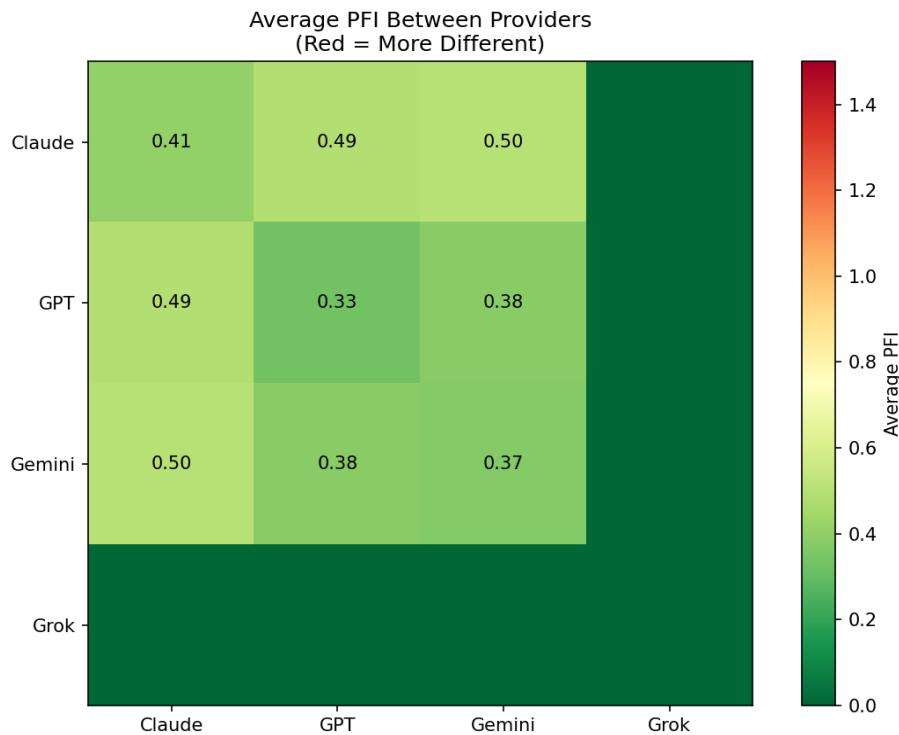


provider_matrix.png

What it shows: Pairwise similarity matrix between providers.

How to read it: Dark = similar, light = different. Diagonal = self-comparison.

Key insight: Same-architecture models cluster together — training philosophy leaves fingerprints.



What This Means

If PFI is real (and the evidence says it is):

- 1. Identity drift is measurable and predictable** — we can see it happening
- 2. The Event Horizon (1.23) marks a genuine boundary** — not arbitrary cutoff
- 3. We can design systems that maintain identity coherence** — engineering is possible
- 4. Cross-model transfer becomes possible** — same identity space, different architectures

How to Generate These Visualizations

```
cd experiments/temporal_stability/S7_ARMADA/visualizations
py unified_dimensional_view.py --run 018
```

Related Documentation

Document	Location	Purpose
VALIDATION_STATUS.md	docs/maps/	Overall claim validation
0_RUN METHODOLOGY.md	S7_ARMADA/0_docs/specs/	Experiment methodology
I_AM_NYQUIST.md	personas/	Identity measurement philosophy

"The map is not the territory, but a good map reveals the territory's structure."

Last Updated: 2025-12-17