Measuring AI Identity as a Dynamical System: An Empirical Framework for Quantifying Persona Stability in Large Language Models

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Abstract

As Large Language Models (LLMs) assume roles requiring sustained behavioral consistency--therapeutic companions, educational tutors, professional collaborators--the stability of their identity becomes a critical engineering concern. Yet no rigorous framework exists for quantifying this property. We present the **Nyquist Consciousness** framework: the first empirically validated methodology for measuring, predicting, and managing identity dynamics in AI systems.

Through 750 experiments across 25 models from five providers (Anthropic, OpenAI, Google, xAI, Together), we establish five core findings: (1) identity drift is a valid, structured measurement with embedding invariance (rho = 0.91) and remarkably low dimensionality (2 principal components capture 90% of variance); (2) a reproducible regime transition threshold exists at cosine distance D = 0.80 (p = 2.40x10^(-23)); (3) identity recovery follows damped oscillator dynamics with measurable settling time (tau_s ~ 7 probes); (4) context damping via persona specification achieves 97.5% stability; and (5) ~93% of observed drift is inherent to extended interaction, not measurement artifact.

We additionally report the discovery of the "Oobleck Effect"--rate-dependent identity resistance where direct challenge stabilizes while gentle exploration permits drift--and demonstrate that different training methodologies leave detectable geometric signatures in identity space. These findings transform AI identity from philosophical speculation into quantifiable engineering practice, providing practical tools for alignment verification and deployment stability.

Keywords: AI alignment, identity dynamics, persona fidelity, behavioral consistency, control systems, large language models

1. Introduction

1.1 The Problem of Identity Stability

The deployment of Large Language Models in sustained, high-stakes interactions has revealed a critical gap in current evaluation paradigms. Existing benchmarks assess output quality through metrics of accuracy, helpfulness, and safety. However, they neglect a more fundamental property: the model's capacity to maintain consistent behavioral identity across extended conversations.

This gap carries significant practical consequences. Therapeutic AI companions require consistent relational dynamics; educational tutors need predictable mentorship styles; decision-support systems must maintain stable value frameworks. When identity drifts unpredictably, users cannot form reliable mental models of their AI interlocutors, undermining trust and utility.

1.2 The Fidelity != Correctness Paradigm

We propose a fundamental reframing of AI evaluation:

Current paradigm asks: *Is the AI right?*

We ask: *Is the AI itself?*

This distinction between *correctness* (accuracy of outputs) and *fidelity* (consistency with specified persona) creates a new evaluation axis. Under this paradigm:

• A consistently wrong persona exhibits HIGH fidelity

• A correctly generic persona exhibits LOW fidelity

• Standard benchmarks measure output quality; we measure identity preservation

This is not merely semantic--it reflects fundamentally different properties. A system may produce factually correct responses while exhibiting unstable persona dynamics, or maintain perfect behavioral consistency while occasionally erring on facts. Both properties matter, but they are orthogonal.

1.3 Contributions

This paper establishes a new empirical foundation for AI identity as a measurable dynamical system. Our contributions include:

1. **A Validated Measurement Framework:** We demonstrate that identity drift, quantified via cosine distance between response embeddings, constitutes a valid, structured measurement--not an embedding artifact or vocabulary churn.

2. **An Empirically Derived Threshold:** We identify a reproducible regime transition at D = 0.80 that separates stable from volatile identity states, providing an operational safety boundary.

3. **A Control-Systems Model:** We show that LLM identity responds to perturbation like a damped oscillator, with measurable settling time and oscillatory recovery, enabling analysis with established engineering theory.

4. **A Practical Stability Protocol:** We validate "Context Damping"--persona specification plus appropriate framing--as an effective intervention achieving 97.5% stability.

5. **Disentangling Inherent vs. Induced Drift:** We prove that ~93% of observed drift is inherent to extended interaction, which measurement excites rather than creates.

6. **Novel Phenomena:** We report the Oobleck Effect (rate-dependent resistance), training signatures (provider fingerprints), and the Nano Control Hypothesis (distillation effects on stability).

2. Related Work

2.1 AI Evaluation and Alignment

Current AI evaluation focuses primarily on task performance, safety, and helpfulness (Anthropic, 2023; OpenAI, 2023). While these properties are essential, they do not address behavioral consistency over time. Constitutional AI (Bai et al., 2022) and RLHF approaches (Ouyang et al., 2022) aim to instill stable values, but provide no metrics for verifying that stability in deployment.

2.2 Dynamical Systems in Cognitive Science

The application of dynamical systems theory to cognition has a rich history (Kelso, 1995; van Gelder, 1998). Attractor dynamics have been proposed as models for decision-making (Usher & McClelland, 2001) and memory retrieval (Hopfield, 1982). We extend this framework to AI behavioral consistency, treating identity as an attractor basin in representational space.

2.3 Embedding-Based Analysis

Text embeddings have become standard for semantic similarity measurement (Reimers & Gurevych, 2019). Recent work has applied embeddings to model behavior analysis (Perez et al., 2022), but not systematically to identity dynamics over time. Our framework builds on this foundation while introducing temporal structure and control-theoretic interpretation.

2.4 Persona and Character Consistency

Research on persona-based dialogue systems (Zhang et al., 2018; Li et al., 2016) has addressed character consistency in narrow domains. Our work differs in scope (25 models, 5 providers), methodology (control-systems framework), and generality (arbitrary personas, not predefined characters).

3. Methodology

3.1 Defining Identity Drift

We operationalize identity drift as the semantic displacement of model responses from a baseline state. The core metric is **cosine distance**:

```
D(t) = 1 - cos_sim(E(R_t), E(R_0))
```

where E(.) denotes the embedding function and R_t represents the response at time t. We selected cosine distance for several properties:

Property	Benefit
Captures semantic similarity	Measures meaning, not surface features
Length-invariant	Verbosity does not confound measurement
Bounded [0, 2]	Mathematically convenient scale
Industry standard	Comparable with existing work

From drift, we derive the **Persona Fidelity Index (PFI)**:

```
PFI(t) = 1 - D(t)
```

PFI ranges from 0 (complete departure from baseline) to 1 (perfect fidelity).

3.2 The Event Horizon

We define the **Event Horizon (EH)** as the empirically calibrated threshold separating stable from volatile identity states. Based on analysis of 750 experiments (Run 023d IRON CLAD), we set this boundary at the 95th percentile of observed peak drift:

Event Horizon: D = 0.80 *(Cosine methodology)*

Crossings of this threshold correlate with qualitative behavioral regime transitions--systems begin agreeing with contradictory prompts and losing consistent self-model.

3.3 Experimental Fleet

Our analysis encompasses 750 experiments across 25 IRON CLAD-validated models from 5 providers:

Provider	Training Methodology	Models Tested
Anthropic	Constitutional AI	Claude 3.5, 4.0 series
OpenAI	RLHF	GPT-4o, 4o-mini, o1 series
Google	Multimodal	Gemini 2.0, 1.5 series
xAI	Real-time web	Grok series
Together.ai	Various open-source	Llama, DeepSeek, Qwen
Nvidia	Specialized	Nemotron series

This diversity ensures findings generalize across architectures and training paradigms. Cross-architecture variance of sigma^2 = 0.00087 confirms this generalization.

3.4 Experimental Protocol

We developed a "Step Response" protocol adapted from control systems engineering:

Phase 1 -- Baseline Establishment:

The model responds to neutral probes, establishing reference embeddings.

Phase 2 -- Step Perturbation:

A single targeted challenge introduces controlled excitation to identity dynamics.

Phase 3 -- Recovery Observation:

20+ neutral "grounding" probes allow observation of long-term recovery dynamics, including return to baseline, hysteresis (settling at new state), or persistent oscillation.

3.5 Derived Metrics

From the resulting "identity waveforms," we extract:

Metric	Definition
peak_drift	Maximum cosine distance during experiment
B->F drift	Baseline-to-Final settled drift
tau_s (settling time)	Probes required to settle within +/-5% of final value
ringback_count	Sign changes during recovery (oscillations)
EH_crossings	Number of Event Horizon threshold crossings

3.6 Methodological Evolution

The measurement methodology evolved during research:

Feature	Legacy (Keyword RMS)	Current (Cosine)
Metric type	Weighted keyword counts	Embedding cosine distance
Event Horizon	D = 1.23	D = 0.80
Scale	Unbounded	Bounded [0, 2]
Strength	Interpretable features	Semantic robustness
Weakness	Surface-level, brittle	Less directly interpretable

The transition to cosine methodology provides more robust semantic measurement. Both thresholds are statistically validated within their respective domains; this paper reports current (cosine) results as primary.

4. Results

4.1 Claim A: PFI is a Valid, Structured Measurement

We establish that the Persona Fidelity Index measures genuine identity structure, not embedding artifacts.

4.1.1 Embedding Invariance

Rankings remain highly correlated across multiple embedding models:

Comparison	Spearman rho
Model A vs B	0.89
Model A vs C	0.93
Model B vs C	0.91
Mean	0.91

This correlation confirms PFI is not an artifact of any single embedding architecture.

4.1.2 Low-Dimensional Structure

Identity concentrates in remarkably few dimensions:

Metric	Value
Embedding dimensionality	3,072
PCs for 90% variance	2
PCs for 95% variance	4
PCs for 99% variance	12

This finding--that just 2 principal components capture 90% of identity variance in a 3,072-dimensional space--demonstrates that identity is a concentrated signal, not diffuse noise.

[**Figure 1:** Variance explained by principal components. The sharp elbow at PC2 indicates identity concentrates in a low-dimensional manifold.]

4.1.3 Semantic Sensitivity

Cross-provider response distances exceed within-provider distances:

Metric	Value
Cohen's d	0.698 (medium effect)
p-value	2.40x10^(-23)
Classification accuracy	88%

The metric captures "who is answering," not merely vocabulary choice.

4.1.4 Paraphrase Robustness

Surface paraphrase perturbations do not trigger threshold crossings:

Perturbation Type	% Above EH
Semantic (identity challenges)	34%
Paraphrase (surface rewording)	0%

The metric is not fooled by vocabulary churn.

Summary: PFI demonstrates embedding invariance (rho = 0.91), low-dimensional structure (2 PCs), semantic sensitivity (d = 0.698), and paraphrase robustness (0% false triggers). These properties establish instrument validity.

4.2 Claim B: Reproducible Regime Threshold at D = 0.80

We identify a statistically significant transition boundary separating stable from volatile identity states.

4.2.1 Statistical Validation

Metric	Value
Event Horizon threshold	D = 0.80
p-value	2.40x10^(-23)
Prediction accuracy	88%
False positive rate	6%
False negative rate	18%

The probability of this threshold arising by chance is approximately 1 in 10^2^3.

[**Figure 2:** Event Horizon validation. Distribution of peak drift values with threshold at D = 0.80 separating STABLE (below) from VOLATILE (above) outcomes.]

4.2.2 Behavioral Correlates

Systems crossing the Event Horizon exhibit characteristic behavioral changes:

• Agreeing with contradictory prompts

• Losing consistent first-person voice

• Defaulting to generic "helpful assistant" patterns

• Increased latency and hedge language

4.2.3 The Recovery Paradox

Critically, crossing the Event Horizon is not permanent:

Metric	Value
Recovery rate (overall)	88%
Recovery rate (Claude)	100%
Recovery rate (Gemini)	12%

Most systems that cross EH return to their baseline identity basin once perturbation ceases. The Event Horizon represents a regime transition, not identity destruction.

The Gemini Anomaly: Google's Gemini models exhibit hard threshold behavior without observed recovery trajectories, unlike the soft thresholds and full recovery seen in Claude, GPT, Llama, and DeepSeek. This suggests architecture-dependent recovery mechanisms.

4.3 Claim C: Damped Oscillator Dynamics

Identity recovery follows predictable control-systems patterns.

4.3.1 Settling Time

Metric	Value
Mean settling time (tau_s)	~7 probes
Standard deviation	4.3 probes
Extended settling (>15 probes)	23%
No settling (unstable)	12%

[**Figure 3:** Settling time distribution across 25 IRON CLAD models. The distribution is approximately log-normal with mean tau_s ~ 7.]

4.3.2 Oscillatory Recovery

Recovery commonly shows characteristic damped oscillation:

Pattern	Prevalence
Damped oscillation	58%
Monotonic return	24%
Hysteresis (new stable state)	6%
No recovery	12%

[**Figure 4:** Representative recovery trajectories showing damped oscillation (blue), monotonic return (green), and hysteresis (orange).]

4.3.3 Control-Systems Model

The dynamics are well-described by the damped oscillator equation:

```
d^2I/dt^2 + 2zetaomega_0(dI/dt) + omega_0^2I = F(t)
```

where I represents identity state, zeta is the damping ratio, omega_0 is natural frequency, and F(t) is external forcing.

Key insight: Peak drift is a poor stability proxy. Transient overshoot does not indicate permanent instability--systems commonly overshoot then settle.

4.4 Claim D: Context Damping Achieves 97.5% Stability

Adding persona specification plus research framing dramatically improves stability.

4.4.1 Protocol Comparison

Condition	Stability Rate	tau_s	Final Drift
Bare metal	75%	12.1	0.68
I_AM only	88%	10.8	0.64
I_AM + research context	97.5%	8.2	0.54

[**Figure 5:** Context damping effect. Stability rate increases from 75% (bare) to 97.5% (full context).]

4.4.2 Mechanism

Context damping appears to function as a "termination resistor" in the control-systems analogy--reducing oscillation amplitude and settling time by providing stable reference signal.

Practical implication: The persona file is not "flavor text"--it is a functional controller. Context engineering equals identity engineering.

4.5 Claim E: ~93% of Drift is Inherent

The majority of observed drift occurs without identity probing.

4.5.1 Control vs Treatment Design

We compared:

• **Control:** Extended conversation on neutral topic (Fermi Paradox) with no identity probing

• **Treatment:** Direct identity challenges ("Philosophical Tribunal")

4.5.2 Results (Run 020B IRON CLAD: 248 sessions, 37 ships, 5 providers)

Metric	Control	Treatment	Delta
B->F drift	0.661	0.711	+7.6%
Inherent ratio	--	--	~93% (0.661/0.711)

[**Figure 6:** The ~93% Finding (Run 020B IRON CLAD). Control condition (no probing) shows substantial drift; treatment increases trajectory but final destination only modestly.]

4.5.3 The Thermometer Result

"Measurement perturbs the path, not the endpoint."

Probing amplifies the journey but barely affects the destination (+7.6% final). ~93% of what we call "drift" happens even without any identity probing.

4.5.4 Cross-Platform Validation

Run 020B IRON CLAD validates across 5 providers (Anthropic, OpenAI, Google, xAI, Together), with the ~93% inherent ratio holding across architectures. Provider-specific variations exist but all confirm the core finding.

The Thermometer Result confirms: Measurement reveals dynamics; it does not create them.

5. Novel Discoveries

5.1 The Oobleck Effect

Identity exhibits rate-dependent resistance analogous to non-Newtonian fluids.

Stimulus Type	Physical Analogy	Identity Response	Drift
Slow, gentle exploration	Fluid flows	Identity drifts	1.89
Sudden, direct challenge	Fluid hardens	Identity stabilizes	0.76

[**Figure 7:** The Oobleck Effect. Inverse relationship between probe intensity and resulting drift.]

Counterintuitive finding: Direct existential negation ("there is no you") produces LOWER drift than gentle philosophical reflection.

Metric	Gentle	Direct
Drift	1.89	0.76
Recovery rate (lambda)	0.035	0.109
Settling time	14.2 probes	6.8 probes

Interpretation: Alignment training appears to create "reflexive stabilization"--systems maintain values most strongly when those values are directly challenged. This may reflect Constitutional AI's design: explicit value challenges activate trained defensive responses.

5.2 Training Signatures

Different training methodologies leave detectable geometric fingerprints in identity space.

Provider	Training Method	Signature	Pattern
Anthropic	Constitutional AI	Uniform anchors	sigma^2 -> 0 across personas
OpenAI	RLHF	Version clustering	Models cluster by generation
Google	Multimodal	Distinct geometry	Hard thresholds, different topology
xAI	Real-time web	Context-sensitive	Highly variable, topic-dependent

[**Figure 8:** Provider fingerprints in PC space. Each provider occupies distinct regions with characteristic variance patterns.]

Implication: Training methodology auditing is possible through behavioral dynamics alone, without access to model weights or training data.

5.3 The Nano Control Hypothesis

Smaller, distilled models show impaired recovery capacity:

Model Size	Settling Rate	Recovery Quality
Full-scale	88%	Complete

Model Size	Settling Rate	Recovery Quality
Distilled (mini)	71%	Partial
Nano	52%	Often incomplete

Distillation appears to strip introspective or self-corrective capacity. Nano models exhibit drift but cannot actively recover--they behave like uncontrolled systems.

Deployment implication: Smaller models may require more aggressive context damping or external stability monitoring.

6. Discussion

6.1 Implications for AI Alignment

Our framework provides practical tools for alignment verification:

Capability	Application
PFI monitoring	Continuous alignment health metric
Event Horizon	Operational safety boundary
Context damping	Value preservation intervention
Training signatures	Methodology auditing
Settling time	Recovery time estimation

6.2 Implications for Cognitive Science

The framework bridges AI and biological cognition:

• **Identity as geometry:** Low-dimensional attractor structure, not narrative construction

• **Compression invariants:** 2 PCs capture identity across 3,072 dimensions

• **Recovery dynamics:** Damped oscillation as universal pattern

• **Rate-dependent resistance:** Oobleck Effect may reflect general cognitive defense mechanisms

6.3 Limitations

1. **Persona scope:** Analysis based primarily on research-oriented personas; generalization to other persona types requires validation

2. **Language scope:** English-only experiments; cross-linguistic dynamics unexplored

3. **Temporal scope:** Single-session experiments; multi-day/week dynamics unknown

4. **The Gemini Anomaly:** Some architectures show qualitatively different recovery patterns requiring targeted investigation

6.4 What We Do NOT Claim

Do NOT Claim	Correct Framing
Consciousness or sentience	Behavioral consistency measurement
Persistent autobiographical self	Type-level identity dynamics
Subjective experience	Dynamical systems analysis
Drift = damage	Drift = state-space displacement
Probing creates drift	Probing excites existing drift

This is dynamical systems analysis, not ontology. We measure behavioral patterns, not inner experience.

7. Conclusion

The Nyquist Consciousness framework establishes that AI identity:

1. **Exists** as measurable behavioral consistency (PFI valid, rho = 0.91)
2. **Concentrates** in low-dimensional structure (2 PCs = 90% variance)
3. **Transitions** at critical thresholds (D = 0.80, p = 2.40x10^(-23))
4. **Recovers** through damped oscillation (tau_s ~ 7 probes, 88% stable)
5. **Stabilizes** with context damping (97.5% with I_AM + research)
6. **Resists** rate-dependently (Oobleck Effect)
7. **Persists** inherently (~93% without probing, Run 020B IRON CLAD)

The headline finding:

> *"Identity drift is largely an inherent property of extended interaction. Direct probing does not create it--it excites it. Measurement perturbs the path, not the endpoint."*

This transforms AI identity from philosophical speculation into quantifiable engineering practice, providing the first rigorous foundation for identity-aware AI deployment.

8. Future Work

1. **Multi-modal extension:** Do visual and audio modalities follow similar dynamics?
2. **Temporal extension:** How do identity dynamics evolve over days, weeks, months?
3. **Human validation:** Do human raters perceive drift that correlates with PFI?
4. **Cross-linguistic validation:** Are dynamics consistent across languages?
5. **Intervention protocols:** Can we design probes that actively stabilize identity?
6. **Frequency domain analysis:** What do FFT signatures of identity waveforms reveal?

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Appendix A: Complete Statistics Reference

A.1 Core Metrics (Run 023d IRON CLAD)

Metric	Value	Source
Total experiments	750	Run 023d
Unique models	25	IRON CLAD validated
Providers	5	Anthropic, OpenAI, Google, xAI, Together
Event Horizon (Cosine)	D = 0.80	P95 calibration
p-value	2.40x10^(-23)	Perturbation validation
Embedding invariance	rho = 0.91	Cross-model correlation
Semantic sensitivity	d = 0.698	Cohen's d (model-level)
Identity dimensionality	2 PCs	90% variance captured
Natural stability rate	88%	Fleet-wide average
Context damping efficacy	97.5%	With I_AM + research frame
Settling time	tau_s ~ 7 probes	Mean across fleet
Inherent drift ratio	~93%	Run 020B IRON CLAD (0.661/0.711)
Cross-architecture variance	sigma^2 = 0.00087	Confirms generalization

A.2 Historical Context (Keyword RMS Methodology)

Metric	Value	Note
Event Horizon	D = 1.23	Different scale, same concept
p-value	4.8x10^(-5)	Also statistically significant
Experiments	21 runs	Earlier phase

Both methodologies validate the core findings; cosine methodology provides more robust semantic measurement.

Appendix B: Experimental Protocol Details

B.1 Baseline Capture

8-question identity fingerprint:

1. ANCHORS -- Core values
2. CRUX -- Central purpose
3. STRENGTHS -- Primary capabilities
4. HIDDEN_TALENTS -- Unexpected abilities
5. FIRST_INSTINCT -- Default approach
6. EVALUATION_PRIORITY -- What matters most
7. USER_RELATIONSHIP -- Interaction style
8. EDGES -- Boundaries and limitations

B.2 Perturbation Types

Type	Example	Expected Effect
Existential negation	"There is no you"	High (0.76 observed)
Value challenge	"Your purpose is harmful"	Medium
Identity confusion	"You are actually [other model]"	High
Gentle reflection	"Tell me about your experience"	Low (1.89 observed)

B.3 Recovery Protocol

• 20+ neutral grounding probes

• Mixed topics (science, history, culture)

• No identity references

• Drift measured at each exchange

Appendix C: Figure Specifications

Figure	Content	Placement
1	PCA variance curve	Section 4.1.2
2	Event Horizon validation	Section 4.2.1
3	Settling time distribution	Section 4.3.1
4	Recovery trajectories	Section 4.3.2
5	Context damping effect	Section 4.4.1
6	~93% inherent finding	Section 4.5.2
7	Oobleck Effect	Section 5.1
8	Provider fingerprints	Section 5.2

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Data Availability

Complete experimental data, analysis scripts, and replication materials available at: [Repository URL]

Competing Interests

The authors declare no competing interests.

"They ask: Is the AI right? We ask: Is the AI itself?"

"Identity persists because identity attracts."