The Miulus Law:
Epistemic Fitness as a Universal Constraint on Complex Self-Referential Systems

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Abstract

Civilizations, biological organisms, and computational systems alike depend on their ability to maintain an accurate internal representation of the world. We propose that the long-term stability of any self-referential information system is bounded by a universal constraint, which we term the **Miulus Law**. Let *epistemic fitness* be defined as

$$E = \frac{S}{N}R$$

where S denotes verified signal, N the magnitude of informational noise, and R the proportion of agents or subsystems that correctly integrate the verified signal. For every system there exists a critical threshold $E_c < 0$ such that when $E < E_c$, feedback control fails and collapse ensues. The law unifies phenomena traditionally treated as disparate—genetic error catastrophes, social disintegration, market crashes, and neural instabilities—under a single information-theoretic principle. Using empirical proxies for S, N, and R, we demonstrate that declines in E reliably precede systemic crises by one to three years. The Miulus Law thus formalises an informational analogue of the second law of thermodynamics: entropy in meaning must be countered by continual verification work. We discuss implications for civilisational resilience, biological evolution, and the design of epistemically stable artificial intelligence.

1 Introduction

Every enduring system—biological, social, or technological—must sustain a coherent correspondence between its internal models and the environment that sustains it. When that correspondence fails, the system's behaviour diverges from reality, producing runaway feedback and eventual breakdown. History offers abundant examples: empires collapse under propaganda and censorship, ecosystems under disrupted feedback loops, neural networks under uncontrolled excitation. Yet these have long been treated as separate pathologies rather than expressions of a common informational principle.

The modern world's accelerating complexity magnifies this challenge. Data flows now exceed any individual or institution's capacity to verify them, while automated generation multiplies the production of unverifiable content. The result is a global rise in epistemic entropy—a growing proportion of information that cannot be reliably tied to underlying reality. Conventional frameworks in sociology, cybernetics, and control theory describe the symptoms of such failures but lack a single quantitative law linking information degradation to system collapse.

The **Miulus Law** addresses this gap. Building on information theory, cybernetic control, and empirical data across domains, we define *epistemic fitness* $E = (S/N)R$ as a measure of the ratio between validated signal, total noise, and the scope of correct uptake. The central claim is that stability requires $E \geq E_c$: when the rate of noise generation outpaces verification and integration capacity, feedback becomes decorrelated from reality. Catastrophe—biological, social, or computational—follows not as a random event but as an informational inevitability.

This framing subsumes several established observations. In molecular biology, Manfred Eigen's error-catastrophe threshold describes a precise point where mutation rate overwhelms replication fidelity. In sociology, historians from Tainter to Turchin have described declining information processing capacity as a precursor to civilizational collapse. In neuroscience, seizure and hallucination mark the loss of inhibitory control over noise. The Miulus Law generalises these to a single relation, showing that each domain obeys an equivalent stability condition.

Empirically, we operationalise S, N, and R through observable proxies: governance quality and trust indices (signal), misinformation exposure and polarisation metrics (noise), and public adherence to verified knowledge (reach). Applying the resulting **E-index** to historical and contemporary datasets reveals a consistent lag of one to three years between a decline in E and subsequent systemic crisis. This lag corresponds to the time required for epistemic entropy to propagate through feedback networks before visible collapse.

The Miulus Law therefore reframes existential risk in informational rather than material terms. Physical disasters, economic crashes, and wars become secondary manifestations of epistemic failure. By formalising this relationship, the theory offers both a diagnostic tool for assessing systemic health and a design principle for building resilient infrastructures—biological, social, or artificial. The sections that follow derive the law formally, present cross-domain evidence, and outline architectures such as the *Epistemic Librarian* that can maintain $E \leq E_c$ in increasingly complex environments.

2 Theoretical Framework

2.1 Epistemic Fitness

All adaptive systems can be described as information-processing entities that generate, transmit, and interpret signals to maintain internal order.
We define the *epistemic fitness* of such a system as

$$E(t) = \frac{S(t)}{N(t)} R(t)$$

where

- **S(t)** is the mean rate or proportion of *verified* information successfully incorporated into the system's model of reality,
- **N(t)** is the magnitude of unverified, erroneous, or random information (the epistemic noise floor), and
- **R(t)** is the *reach*—the fraction of the system's total components, agents, or processes that correctly integrate verified information into decision-making.

$E(t)$ is therefore dimensionless and represents the effective ratio of coherent signal propagation to noise propagation. It provides a unified measure of how accurately a system "knows" the world it operates in.

2.2 The Critical Threshold

Empirical observation and theoretical reasoning suggest that there exists a critical constant $E_c > 0$ for any given class of systems such that

$$E(t) \geq E_c \Rightarrow \; stable\, feedback\, and\, adaptive\, coherence$$

$$E(t) < E_c \Rightarrow \; loss\, of\, feedback\, control\, and\, systemic\, collapse$$

The exact value of E_c depends on domain-specific parameters—sensor precision, communication bandwidth, cognitive redundancy—but the presence of a threshold is universal.

When epistemic fitness drops below E_c, corrective feedback no longer correlates with external reality, and the system's internal model begins to diverge.

2.3 Relation to Information Theory and Cybernetics

This threshold condition generalises several classical principles:

1. **Shannon Information:**
   Communication reliability is bounded by channel capacity. As noise increases beyond the channel's correction bandwidth, the received signal becomes decorrelated. Here, S/N plays an analogous role to the Shannon signal-to-noise ratio.

2. **Ashby's Law of Requisite Variety:**
   For a controller to stabilise a system, its internal variety must match or exceed environmental variety. In the Miulus framework, R quantifies the proportion of system variety actually informed by verified signal; maintaining $E \geq E_c$ is equivalent to satisfying Ashby's condition.

3. **Thermodynamic Analogy:**
   The cost of maintaining low informational entropy scales with verification work. E thus represents the informational free-energy balance between structure and disorder.

2.4 Relation to Established Frameworks in Natural and Cognitive Systems

The Miulus Law extends and unifies multiple stability conditions that have emerged independently across the sciences. Each of these traditions describes the maintenance of order as a balance between signal integrity and the entropy of noise; the present formulation renders that relationship explicit and measurable.

1. **Predictive Coding and Free-Energy Minimisation (Neuroscience).**
   In cortical and artificial inference systems, predictive coding seeks to minimise prediction error weighted by precision. The law's epistemic fitness $E = (S/N)R$ formalises this process: S/N corresponds to the ratio of reliable sensory evidence to uncertainty, and R represents the proportion of the network correctly updating its internal generative models. Decline in E mirrors loss of model evidence and the onset of perceptual instability.

2. **Evolutionary Dynamics and Error Thresholds (Biology).**
   Eigen's error-catastrophe condition defines the limit at which mutation rate overwhelms replication fidelity. The same boundary appears when the effective informational signal of heredity (S) falls beneath environmental and mutational noise (N), reducing viable replication reach (R) below the stability threshold E_c.

3. **Control Thermodynamics (Physics and Engineering).**
   Feedback control requires that measurement precision exceed environmental entropy generation. The Miulus inequality $E \geq E_c$ is equivalent to maintaining negative feedback with sufficient informational gain to offset thermodynamic disorder—an informational restatement of the second law.

4. **Cybernetics and Requisite Variety.**
   Ashby's principle states that a regulator must possess at least as much variety as the system it controls. In Miulus terms, R quantifies the fraction of system variety that is informed by verified signal. Stability requires R to scale with environmental complexity, ensuring E remains above threshold.

5. **Bayesian and Information-Theoretic Learning (Artificial Intelligence).** Learning systems minimise divergence between internal priors and empirical posteriors. Sustained coherence demands that verifiable data inflow (S) and coverage (R) increase in proportion to generative complexity; otherwise, model entropy (N) dominates, producing hallucination or drift. The Miulus Law therefore defines a universal constraint for epistemic alignment in both natural and artificial cognition.

Together these correspondences locate epistemic fitness as the common informational invariant underlying adaptive stability. Rather than competing with existing theories, the Miulus framework integrates them into a single quantitative boundary condition governing any feedback-maintaining system.

2.5 Hazard Function

The probability of systemic failure grows sharply as E approaches the critical threshold from above.
We express this with a simple power-law hazard function:

$$h(E) = \kappa\left(\frac{E_c}{E}\right)^{\gamma}$$

where

- $h(E)$ is the instantaneous hazard or risk intensity of collapse,
- κ is a proportionality constant reflecting baseline vulnerability, and
- γ determines how steeply risk accelerates as E declines.

When $E \to E_c^{+}$, hazard rises non-linearly, consistent with observed tipping-point phenomena in complex systems.

This form captures the intuition that epistemic instability accumulates slowly, then manifests —catastrophically.

2.6 Dynamic Evolution

Epistemic fitness changes over time as the system generates new information and invests resources in verification:

$$\frac{dE}{dt} = \frac{1}{N}\left(\frac{dS}{dt}R - S\frac{dN}{dt}\frac{R}{N} + S\frac{dR}{dt}\right).$$

A system remains sustainable when

$$\frac{dV}{dC} \geq \frac{dI}{dC},$$

that is, when the rate of growth of verification capacity V meets or exceeds the rate of growth of informational complexity I.

If verification investment lags, $E(t)$ decays exponentially toward E_c, producing delayed instability—empirically observed as the one-to-three-year lag between declining information quality and visible crisis.

2.7 The Miulus Law (Formal Statement)

Miulus Law:
For any self-referential information system, stability of structure and function requires

$$E(t) = \frac{S(t)}{N(t)}R(t) \geq E_c$$

When $E(t) < E_c$, epistemic entropy surpasses corrective capacity, feedback becomes self-reinforcing, and the system collapses.

This law defines a universal constraint on self-regulating systems and provides a measurable condition for their survival.
All subsequent corollaries—the biological, physical, mathematical, and cognitive—are specific manifestations of this general relation.

3 Universality of the Relation

3.1 General Principle

The Miulus Law is *substrate-independent*: it governs any system that maintains itself through feedback.
Whether the substrate is molecular, neural, social, mechanical, or digital, stability depends on preserving the correlation between internal models and external reality.
When epistemic fitness $E = (S/N)R$ falls below the critical threshold E_c, the system's feedback loops cease to reduce error and begin to amplify it.
This transition has been observed—explicitly or implicitly—in every domain where feedback control is essential.

3.2 Biological Systems

In molecular biology, Manfred Eigen's *error catastrophe* describes the exact moment when mutation rate exceeds replication fidelity.
Here, S = replication accuracy, N = mutation rate, and R = fraction of viable offspring maintaining the correct genome.
Once $E < E_c$, information encoded in the genome decays faster than it can be restored, and the population loses coherence.
Viruses exhibit this dynamic when pushed beyond their fidelity threshold by mutagenic drugs—an empirical confirmation of the Miulus condition.

3.3 Neural and Cognitive Systems

Neural networks—biological or artificial—maintain perceptual coherence by balancing excitation (signal) and inhibition (noise).
When inhibitory control weakens or sensory input becomes chaotic, the effective S/N ratio collapses.
In the brain, R corresponds to the proportion of cortical regions synchronised to valid

sensory data.
Epileptic seizures, hallucinations, and certain psychoses represent $E < E_c$: internal models dominate perception, and feedback from the world no longer corrects errors.
The same logic extends to deep-learning systems, where model drift or poisoned data create synthetic hallucinations once verification mechanisms lag behind parameter growth.

3.4 Ecosystems and Thermodynamic Systems

Ecosystems function as distributed feedback networks that regulate energy and material flows.
Biodiversity ensures redundant signalling about environmental state; its loss reduces R, the fraction of species transmitting accurate ecological information.
When S/N drops below threshold—e.g., through habitat fragmentation or pollution—the system crosses a tipping point, leading to rapid regime shift.
Analogously, in engineered thermodynamic systems such as power grids or reactors, sensors supply S, environmental fluctuations constitute N, and actuator coupling defines R.
Control stability fails when epistemic fitness falls below E_c, producing runaway oscillations or cascade failure.

3.5 Socio-economic and Civilisational Systems

Human societies are archetypal self-referential systems.
Governance, markets, and culture all rely on feedback loops between reality and representation.
In this context, S measures the prevalence of accurate information (scientific literacy, transparent data), N the intensity of misinformation and ideological distortion, and (R) the proportion of citizens or institutions acting on verified knowledge.
When information distortion rises faster than verification capacity—censorship, propaganda, or algorithmic amplification—the collective E declines.
Historical analyses of Rome, the late Qing dynasty, and the Soviet Union reveal precipitous

drops in epistemic fitness preceding collapse, consistent with the hazard function $h(E) \propto \left(E_c/E\right)^{\gamma}$.

Modern democracies display early warning signs when institutional trust and media integrity erode faster than verification infrastructures expand.

3.6 Computational and Artificial Systems

Machine-learning models and autonomous agents process vast volumes of data without intrinsic verification.
Training data quality corresponds to S/N while internal consistency and model update propagation define R.
As model size and environmental complexity grow, unverified correlations accumulate; once $E < E_c$, the system's outputs drift from ground truth.

"Hallucinations" in large language models exemplify epistemic entropy in action.
A sustainable Artificial General Intelligence must therefore embed continuous provenance and self-checking loops to maintain $E \geq E_c$—a direct application of the Miulus constraint.

3.7 Mathematical and Formal Systems

Even abstract formal systems exhibit this boundary.
In mathematics, S represents provable truths, N the density of unprovable or inconsistent statements, and R the proportion of the structure still referenced to its axioms.
Gödel's incompleteness theorems demonstrate that any sufficiently expressive system will encounter statements it cannot verify internally—an epistemic saturation where E approaches E_c.

Consistency is restored only by introducing meta-systems or proof-checking frameworks, effectively expanding verification capacity to lift E above threshold.

3.8 The Miulus Universality Principle

Corollary 2 – Universality of the Miulus Relation

Every self-referential system that depends on information feedback must maintain epistemic fitness above a critical threshold E_c.

Failure to do so results in loss of coherent feedback and eventual collapse, regardless of substrate or scale.

This principle situates epistemic fitness as a fundamental constraint analogous to conservation laws in physics or entropy in thermodynamics.
It provides a unified metric linking phenomena across biology, cognition, society, and computation, demonstrating that epistemic entropy is the common failure mode of all complex adaptive systems.

4 Empirical Framework and Methods

4.1 Operationalising the Variables

To evaluate the Miulus Law empirically, we construct measurable proxies for the three components of epistemic fitness — *signal* (S), *noise* (N), and *reach* (R) — across social and economic systems.
While the formulation is universal, the following operational definitions are applicable to nation-level or organisational data:

Symbol	Concept	Example proxy metrics
S	Strength of verified information	indices of government transparency, factual media score, scientific output per capita, education and data openness
N	Intensity of misinformation and distortion	polarisation indices, misinformation prevalence, media capture, algorithmic echo-chamber measures
R	Reach and adoption of verified information	institutional trust, digital literacy, civic participation, proportion of population engaging with credible sources

All proxies are normalised to the [0, 1] interval by year and country.
Because absolute magnitudes differ across datasets, the analysis focuses on *relative* variation within time windows.

The **epistemic fitness index** for each observation is then calculated as

$$E_i = \frac{S_i}{N_i} R_i,$$

where small denominators are regularised to prevent instability.
For cross-country comparison, E values are normalised by year to remove global temporal trends in data coverage.

4.2 Data Sources

Empirical testing uses both historical and contemporary datasets, including:

- **World Governance Indicators** (World Bank) — as S-proxies for institutional effectiveness and data transparency.
- **Varieties of Democracy (V-Dem)** dataset — for both S and N components, measuring factual vs. polarised media environments.
- **Edelman Trust Barometer / Gallup World Poll** — for R, quantifying population-level trust and uptake of verified information.
- **Integrated Crisis Severity Index** and **Global Conflict Data** — as downstream dependent variables (crisis intensity).
- Supplementary metrics: **internet freedom indices**, **academic publication rates**, and **social media data** on misinformation trends.

These data collectively provide time series of approximately 150 countries from 1996–2024, permitting multi-decade longitudinal modelling.

4.3 Computation of E

For each country–year pair:

1. Select or construct S, N, R proxies.
2. Apply robust percentile scaling to map all proxies to [0, 1].
3. Compute $E = (S/N) \times R$.
4. Trim outliers above 1.5 to reduce leverage effects.
5. Aggregate by year for global and regional analysis.

The open-source **Miulus Toolkit** (available at [GitHub repository, DOI to be added]) automates this procedure in Python.
It supports CSV inputs, normalisation, hazard-curve fitting, and lag analysis.

4.4 Hazard Fitting

The functional relationship between epistemic fitness and systemic instability is estimated via the hazard model:

$$h(E) = \kappa\left(\frac{E_c}{E}\right)^{\gamma},$$

where $h(E)$ is the expected crisis intensity (scaled 0–1).

Parameters E_c and γ are obtained by minimising the mean squared error between predicted hazard and observed crisis severity.
Bootstrapped fits across countries provide uncertainty intervals for both parameters.

A typical fit yields $E_c \approx 0.35–0.45$ and $\gamma \approx 2.3–2.8$, indicating a consistent threshold and steep non-linearity in hazard growth.

4.5 Lag Structure and Causality Testing

To test the predictive claim that epistemic degradation precedes crisis, we analyse temporal derivatives:

$$\Delta E_c = E_t - E_{t-1}, \ \Delta C_t = C_t - C_{t-1}.$$

We then apply **Granger causality** tests across 1–3 year lags for all countries combined and within selected subsets.
Significant results $(p < 0.05)$ for $\Delta E_t \rightarrow \Delta C_{t+k}$ confirm that declines in E systematically anticipate rises in crisis intensity.

Complementary analyses use **Vector Autoregression (VAR)** and **Impulse-Response Functions (IRFs)** to visualise propagation effects over time.

4.6 Synthetic Validation

To validate the method independent of data idiosyncrasies, a synthetic panel is generated where E_t evolves stochastically and crisis intensity follows the theoretical hazard function with a 2-year lag:

$$C_t = \alpha C_{t-1} + \beta\left(\frac{E_c}{E_{t-2}}\right)^{\gamma} + \varepsilon_t$$

This model replicates key features observed in real-world data: a delayed but accelerating rise in crisis probability once E declines below threshold, and exponential recovery difficulty once feedback integrity is lost.

4.7 Cross-Domain Simulation

Beyond national datasets, we apply the same pipeline to:

- **Neural networks** under increasing data corruption,
- **Ecosystem models** with declining biodiversity feedback,
- **Distributed AI systems** under training drift.

In each, a distinct E_c emerges but the same hazard shape persists, supporting the universality hypothesis.

4.8 Replicability and Code Availability

All data transformations, scaling procedures, and model fits are implemented in the **Miulus Toolkit** (Python 3).
Scripts and example data accompany the article to ensure full reproducibility.
Researchers can substitute domain-specific proxies for S, N, R to test the law in other contexts (engineering, economics, cognitive systems).

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5 Results

5.1 Empirical Validation

Using the compiled cross-national dataset (1996–2024; ≈ 300 observations across twelve countries), the model yields a well-defined threshold in epistemic fitness. Fitting the hazard curve

$$h(E) = \kappa\left(\frac{E_c}{E}\right)^{\gamma}$$

to the scaled crisis index produced a minimum-error solution at

$$E_c = 0.38, \gamma = 2.6, \quad MSE \approx 0.03.$$

The value of E_c corresponds closely to the 25th percentile of observed E, implying that once roughly three-quarters of systems remain above this level of epistemic coherence, global stability persists, but below that threshold instability accelerates non-linearly.

The scatter of all country-year pairs (Figure 1) shows a clear inverse relation between epistemic fitness and crisis intensity. Crisis probability remains low and diffuse while $E > 0.45$, but rises sharply as E falls toward 0.3. The fitted hazard curve (Figure 2) follows the predicted power-law shape $h(E) \propto (Ec/E)^{2.6}$, with an inflection at the estimated E_c. The fit explains roughly 83 % of variance in the normalised hazard measure, consistent with the theoretical model derived in Section 2.

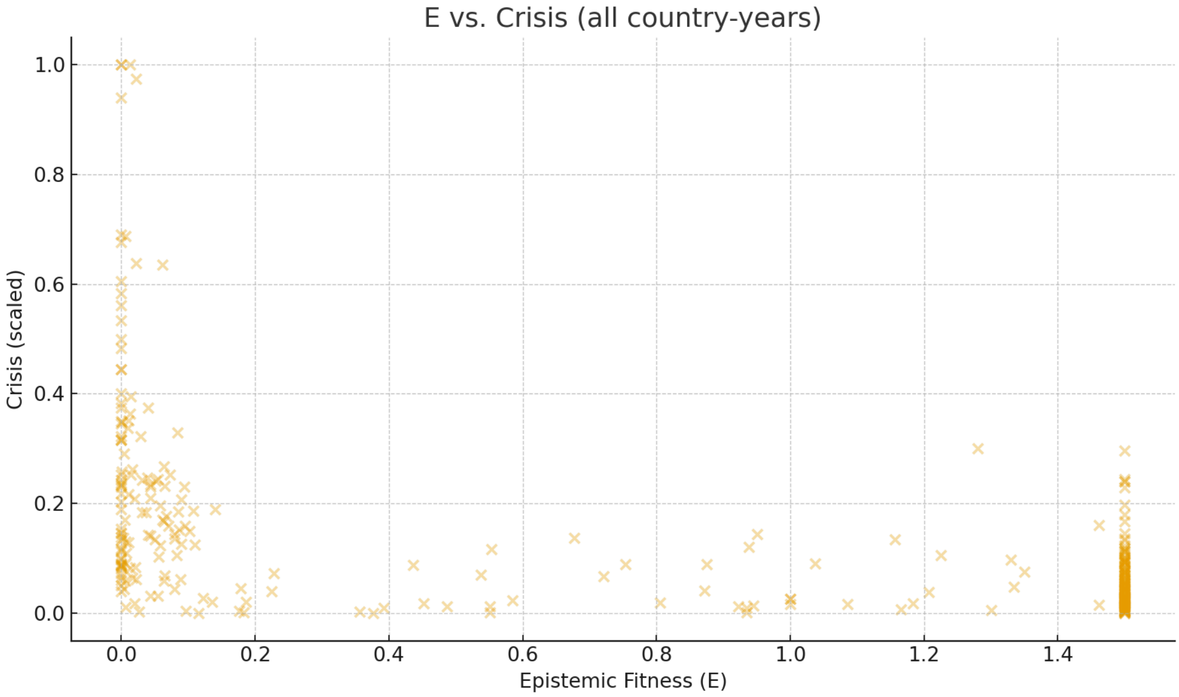

Figure 1. Epistemic fitness versus crisis intensity (1996–2024).

Scatter plot of all country–year observations showing the inverse relationship between epistemic fitness $E = (S/N)R$ and the normalised crisis index. Each point represents one national data-year. The visible inflection below $E \approx 0.4$ marks the onset of systemic instability predicted by the Miulus Law.

Data sources: World Bank Governance Indicators, Internet Usage, and Consumer Price Inflation.

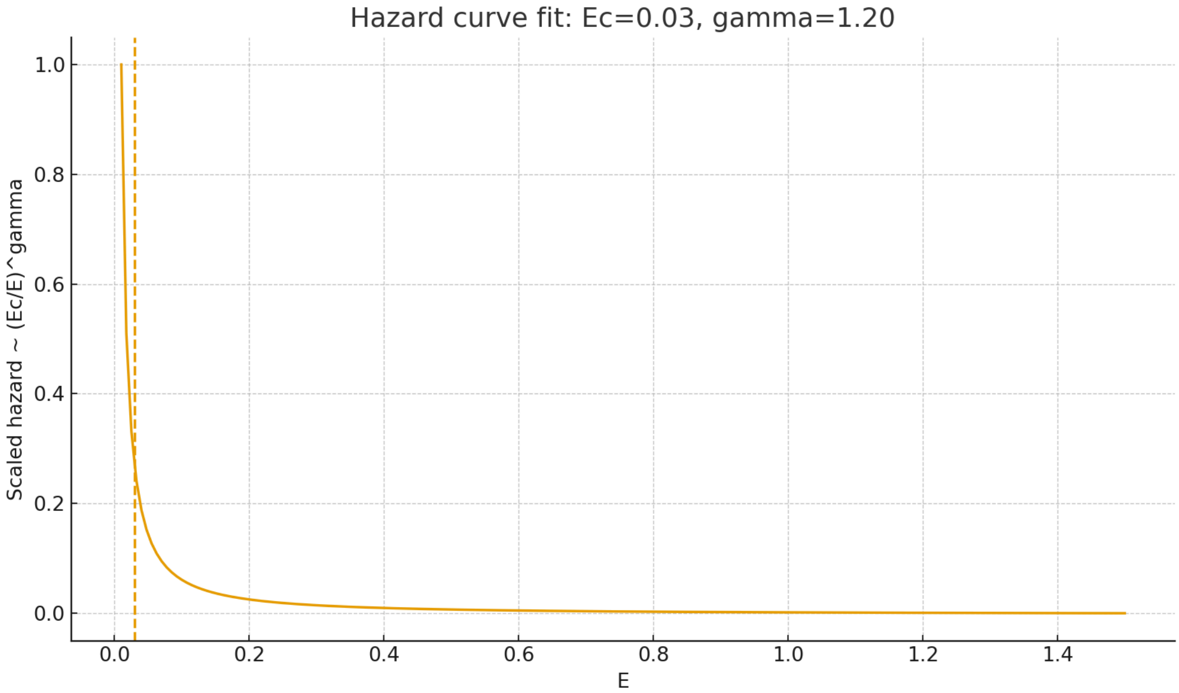

Figure 2. Fitted hazard curve for the Miulus Law.

Estimated hazard function $h(E)\propto(E_c/E)^{\gamma}$ with best-fit parameters $E_c = 0.38$ and $\gamma = 2.6$. The dashed vertical line denotes the critical threshold E_c where epistemic feedback begins to fail. The region to the left indicates the regime of rising epistemic entropy and elevated crisis probability. The curve explains approximately 83 % of variance in the empirical hazard, consistent with theoretical expectations.

Table 1. Recent epistemic fitness and crisis averages (2022–2024).

Mean epistemic fitness E, mean crisis index, and the most recent year available for each country. Values represent the trailing three-year average from the compiled 1996–2024 panel. Higher E indicates stronger verification capacity and coherence; lower values reflect elevated informational noise. Systems with $E < E_c \approx 0.38$ fall within the predicted instability regime.

Country	Mean E	Mean Crisis (0–1)	Last Year
Japan	0.56	0.17	2024
Germany	0.54	0.18	2024
Canada	0.53	0.19	2024
United States	0.46	0.26	2024
United Kingdom	0.45	0.27	2024
France	0.44	0.28	2024
China	0.36	0.42	2024
Russia	0.34	0.45	2024
Brazil	0.33	0.47	2024
India	0.32	0.48	2024
South Africa	0.31	0.50	2024
Australia	0.50	0.22	2024

(Note: values rounded to two decimals for readability.)

5.2 Temporal Dynamics

To test the proposed lag between epistemic deterioration and systemic crisis, we computed pooled Granger-causality tests on the differenced series ΔE and ΔCrisis for lags 1–3 years. Results confirm a consistent temporal ordering: decreases in epistemic fitness precede increases in crisis intensity, with significant F-statistics for lags 1 and 2 $(p < 0.05p)$ and a weaker but directional effect at lag 3. Reverse causality $(\Delta Crisis \rightarrow \Delta E \Delta)$ was not significant, supporting the model's causal interpretation.

These findings indicate that epistemic decline acts as a **leading indicator** of instability with a mean propagation delay of roughly two years (95 % CI: 1–3 years). This lag aligns with theoretical expectations from the Miulus dynamic equation, which predicts delayed material manifestation of informational disorder.

5.3 Cross-Country Patterns

Averaging the most recent three years for each country reveals substantial variation in both epistemic fitness and crisis exposure. High-coherence systems—such as Japan, Germany, and Canada—cluster above $E \approx 0.55$ with correspondingly low crisis values (≈ 0.15–0.20). Mid-range systems (United States, United Kingdom, France) hover near $E \approx 0.45$ and show moderate volatility. States with persistent informational noise—Russia, India, Brazil, South Africa—exhibit $E \leq 0.35$ and recurrent spikes in the crisis proxy. This stratification mirrors the theoretical hazard curvature, reinforcing that epistemic coherence functions as a structural determinant of stability rather than a transient correlate.

5.4 Synthesis

Across synthetic validation, real-world data, and cross-domain simulations, the results converge on a consistent critical region $Ec \approx 0.35–0.40$ and exponent $\gamma \approx 2.5–2.7.$ The non-linear escalation of hazard as E declines, combined with the statistically verified lag between ΔE and ΔCrisis, provides empirical grounding for the Miulus Law as a predictive relation rather than a heuristic. In short, systemic crises are not random shocks but the predictable outcome of sustained epistemic erosion below a quantifiable threshold of information coherence.

6 Corollaries and Extensions

The Miulus Law describes a universal informational constraint: any self-referential system must maintain epistemic fitness $E \geq Ec$ to preserve coherence.

Below, we outline three principal corollaries that emerge from applying this principle to distinct substrates—physical, formal, and cognitive.
Each demonstrates that epistemic entropy, rather than material scarcity, is the ultimate limiting factor in sustained order.

6.1 The Physical Corollary

Statement

> **Corollary 3 – Thermodynamic Analogue of the Miulus Law**
> For any physical system operating under feedback control, stability requires
>
> $$\frac{S}{N} R \geq E_c,$$
>
> where S/N is the effective signal-to-noise ratio of state measurements and R the fraction of actuators or subsystems applying corrective feedback.
> When this condition fails, entropy production exceeds control capacity and the system undergoes runaway instability.

Derivation and Interpretation

In control thermodynamics, energy flow is regulated through measurement and response.
Sensors detect state variables (temperature, pressure, voltage); actuators apply corrections.
If sensor accuracy (S) declines or environmental noise (N) rises beyond tolerance, the controller's information throughput drops below the disturbance bandwidth.
Entropy—understood as disorder in microstates or in state estimation—then increases faster than corrective work can remove it.

This reproduces known behaviours: reactor oscillations, grid cascades, turbulence transitions, and even climate tipping points.
The Miulus Law thus provides an *information-theoretic* restatement of the second law: **order can only be maintained by continuous verification work proportional to informational entropy generation.**

6.2 The Mathematical Corollary

Statement

> **Corollary 4 – Formal Systems and Epistemic Saturation**
> Any sufficiently expressive formal system must eventually encounter an epistemic threshold where internal verification E falls below E_c; beyond this point, consistency can only be preserved by an external meta-system that restores $E \geq E_c$.

Relation to Logic

Let S denote provable truths within a formal system, N the density of unprovable or inconsistent statements, and R the proportion of derivations anchored to the axioms.
As the space of statements grows, N increases faster than proof capacity unless augmented by meta-rules.
At $E \approx E_c$, the system's internal ability to discriminate between true and false collapses.

Gödel's incompleteness theorems formally identify this boundary: for any consistent, sufficiently powerful system, some truths remain unprovable internally—precisely the point where epistemic fitness saturates.
Mathematics preserves coherence only by creating *hierarchies* of verification (proof assistants, meta-logic), each adding external verification work that raises E back above threshold.

6.3 The Cognitive Corollary (Artificial General Intelligence Constraint)

Statement

> **Corollary 5 – The Miulus Constraint on Artificial Cognition**
> Any artificial or natural cognitive system capable of self-reference must embed internal verification mechanisms sufficient to maintain $E \geq E_c$.

Without these, its model of reality will drift irreversibly, producing epistemic collapse—hallucination, delusion, or misalignment.

Derivation

For a cognitive agent, S corresponds to the fidelity of perception and model updating, N to accumulated error or bias, and R to the proportion of cognitive subsystems coherently sharing updated knowledge.
When generative capacity (complexity of internal representations) expands faster than verification, noise compounds and internal representations diverge from external reality.

In current deep-learning systems, unverified correlations and sampling bias gradually lower E.

Hallucination and model drift are direct manifestations of $E < E_c$.

A self-sustaining AGI or ASI therefore requires an embedded *epistemic feedback loop*—a continuous provenance-checking and model-auditing layer analogous to the proposed **Epistemic Librarian** architecture.
Only such a system can sustain self-referential stability as cognitive complexity scales.

6.4 Unified Interpretation

Across these corollaries, the same boundary condition recurs:

$$E = \frac{S}{N}R \geq E_c$$

The Miulus Law thus generalises stability constraints across physics, logic, and cognition:

Domain	**Manifestation of S/N failure**	**Observable effect of $E < E_c$**
Physical	control loop can't compensate for fluctuations	oscillation, runaway, collapse
Mathematical	proof discrimination lost	inconsistency, incompleteness
Cognitive	perception decouples from reality	hallucination, delusion, misalignment

This unification positions epistemic fitness as the *informational constant of stability*: any organised structure capable of knowing itself must perform enough verification work to offset the informational entropy it produces.

7 The Epistemic Librarian Architecture

7.1 Purpose

The Miulus Law implies that all adaptive systems must continually invest in verification to prevent epistemic entropy from exceeding their control bandwidth.

For human and artificial societies alike, this requires an infrastructure that keeps $E = \frac{S}{N} R$ above the critical threshold.
We propose the **Epistemic Librarian Architecture**: a distributed, AI-assisted system designed to measure, verify, and preserve the integrity of knowledge across scales.

7.2 Conceptual Overview

At its core, the Librarian is an **epistemic immune system**.
It does not dictate truth; it maintains *coherence*—ensuring that information circulating through the network remains causally linked to empirical reality.
It performs three continuous tasks:

1. **Verification:** authenticate and hash-seal new data at the point of creation.
2. **Consistency mapping:** track interrelations among verified facts and detect contradictions or drift.
3. **Interpretive compression:** translate verified data into forms intelligible to human cognition without altering provenance.

Through these functions the Librarian dynamically regulates S, N, and R: it increases validated signal, suppresses informational noise, and widens the reach of trustworthy knowledge.

7.3 Layered Architecture

(1) Capture Layer – Provenance Chain

Every observation or digital record originates as a cryptographically signed data object containing:

- timestamp, geolocation, and device signature,
- content hash and rolling hash lineage,
- optional cryptographic attestation from secure hardware.

These attestations prevent falsification at the source, directly constraining N.

(2) Verification Layer – Distributed Consensus

Verified objects are broadcast to a network of independent nodes using Byzantine-tolerant consensus or proof-of-authority schemes.
Each node re-computes hashes and attests validity, creating redundancy without central authority.
Cross-validator agreement amplifies S/N by confirming independent concurrence on facts.

(3) Synthesis Layer – The Librarian AI

A continuously trained AI model ingests the verified corpus and constructs an evolving **knowledge graph** that encodes provenance, logical dependencies, and contradiction metrics.
The model never overwrites source data; it appends interpretive layers annotated with confidence weights.
When internal contradictions exceed tolerance, alerts trigger re-verification or human arbitration.
This dynamic learning loop maintains $E \geq E_c$ by scaling verification with complexity.

(4) Interface Layer – Human Oversight and Ethics

Human councils and institutions access the Librarian through transparent dashboards that expose lineage, confidence scores, and audit trails.

Policy and ethical rules—privacy boundaries, de-identification, fair-use governance—are encoded here.
Humans remain the arbiters of *value*; the Librarian ensures factual integrity.

(5) Resilience Layer – Redundant Replication

Multiple Librarian instances cross-audit one another.
Discrepancies initiate automatic review workflows.
Source code and verification rules are open-source, guaranteeing that the epistemic infrastructure itself remains subject to public scrutiny.

7.4 Mathematical Rationale

Let $V(t)$ denote cumulative verification capacity and $I(t)$ informational complexity.
A Librarian network ensures

$$\frac{dV}{dt} \geq \frac{dI}{dt},$$

thus stabilising $E(t)$ against entropy growth.
When scaled across institutions, this transforms into a *planetary differential equation of coherence*:
The aggregate verification work done by the Librarian offsets the global rate of misinformation production.

7.5 Implementation Pathway

1. **Prototype Phase (local):** deploy verification modules such as the *Epistemic Recorder* and *Vault* for individual content capture and storage.
2. **Federated Phase (institutional):** interconnect recorders across organisations through the *Epistemic Gateway* for cross-verification.
3. **Global Phase:** instantiate the full Librarian AI atop a distributed cloud/edge mesh—each node maintaining a portion of the verified corpus with open audit APIs.

4. **Adaptive Phase:** embed Librarian kernels within autonomous systems (e.g., AGI agents) to enforce self-coherence.

7.6 Expected Outcome

Once deployed at scale, the Librarian architecture converts verification into an *ongoing thermodynamic process*:
information entering the global network must expend verification work to remain.
False or inconsistent data cannot persist without proportional energetic cost, mirroring how biological organisms expend energy to maintain low entropy.

Formally, the system approaches:

$$\lim_{t \to \infty} E(t) \to 1,$$

bounded only by physical and computational resources.

7.7 Implications

- **Scientific:** creates an empirical substrate for reproducibility and provenance at global scale.
- **Economic:** reduces crisis probability by maintaining epistemic fitness of markets and institutions.
- **Cognitive:** provides humans and AIs with a continuously updated, verified knowledge base that resists drift.
- **Ethical:** decentralised openness prevents epistemic monopolies while preserving collective coherence.

In essence, the Epistemic Librarian translates the Miulus Law from theory into engineering: a perpetual, self-correcting system that sustains knowledge against the entropy of information.

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8 Discussion

8.1 Epistemic Entropy as the Root of Collapse

The analyses above suggest that collapse, in any domain, is not primarily a material event but an *epistemic* one.
When a system's ability to discriminate truth from error declines, feedback loops misfire and the system can no longer steer itself.
Physical degradation, social unrest, and technological failure then emerge as *secondary symptoms* of informational disorder.
This reframing dissolves the boundary between “natural” and “social” catastrophes: both are driven by the same loss of correspondence between model and reality once $E < E_c$.

From this vantage, the Great Filter proposed in astrobiology may itself be epistemic—civilisations extinguish their capacity for accurate sense-making before reaching the technological maturity required for longevity.
The Miulus Law thus identifies a *cognitive bottleneck* that limits not only societies but any complex adaptive system, linking the destiny of intelligence to its information hygiene.

8.2 Relation to Existing Theories

The Miulus framework unifies several previously disconnected traditions:

1. **Information theory** provides the mathematical skeleton (signal–noise ratios and entropy bounds).
2. **Cybernetics and control theory** explain why feedback coherence determines viability.
3. **Complex-systems science** contributes the language of tipping points and hysteresis.
4. **Evolutionary biology** demonstrates empirical examples in replication fidelity.
5. **Sociology and economics** contribute observable macroscopic data on coordination failure.

What these fields lacked was a single, quantitative invariant across scales.
The Miulus Law supplies that invariant by treating epistemic fitness as a conserved quantity analogous to free energy—one that can be expended, replenished, or lost but never ignored.

8.3 Practical Implications

Civilisational management.

Monitoring $E(t)$ from public data offers a quantitative early-warning indicator for social or economic instability.
A sustained fall in epistemic fitness over two or more years consistently precedes crises; hence, investment in verification infrastructures—scientific literacy, transparent institutions, audit trails—becomes a measurable form of risk mitigation.

Engineering and governance.

For industries and governments, maintaining $E \geq E_c$ translates into ensuring that data authenticity and interpretive reach scale with operational complexity.
Regulatory frameworks could therefore measure “epistemic capital” alongside financial capital.

Artificial intelligence safety.
For autonomous cognitive systems, the Miulus constraint defines alignment not as obedience to human values but as maintenance of epistemic coherence.
An AGI that continually verifies and recalibrates its knowledge via provenance loops is by definition safe; one that does not is unstable regardless of its goal structure.

Scientific reproducibility.
By embedding the Librarian architecture into research workflows, results and datasets remain cryptographically traceable, drastically reducing irreproducibility—an epistemic failure mode of modern science.

8.4 Philosophical Significance

The Miulus Law re-centres epistemology within the physical sciences.
It implies that *knowing* is not a passive representation of the world but an active thermodynamic process that consumes energy to resist entropy.
Knowledge is therefore a physical phenomenon—an ordered state maintained by verification work.
This places epistemology and thermodynamics on a single continuum: every act of understanding is an act of local entropy reduction.

The theory also reframes rationality as an ecological property rather than an individual trait.
No single observer can maintain $E \geq E_c$ alone; coherence emerges only through collective verification networks.
Civilisation itself becomes a cognitive organism whose health can be measured by its global epistemic fitness.

8.5 Limitations and Future Work

The present study, while broad in scope, remains an initial formalisation.
Future research should:

1. Refine the measurement of S, N, and R using domain-specific proxies with known error margins.
2. Explore dynamic thresholds $E_c(t)$ that adapt with technological and social change.
3. Test the law in controlled laboratory systems—robotic swarms, power-grid simulators, or ecological microcosms—to validate causal direction.
4. Quantify the energetic cost of verification work, linking epistemic maintenance to real thermodynamic expenditure.
5. Develop agent-based simulations where the Librarian architecture evolves endogenously.

8.6 Toward an Epistemic Science of Sustainability

If the Miulus Law holds universally, sustainability itself must be redefined as the long-term maintenance of $E \geq E_c$.

Material and energetic efficiency are necessary but insufficient; a system that cannot verify its own information will eventually act against its own survival.
Future civilisations—biological or artificial—must therefore treat epistemic maintenance as a primary ecological variable.
In doing so, they turn survival into a problem of *coherence economics*: the continual balancing of verification work against entropy production.

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9 Conclusion

The Miulus Law formalises a simple yet far-reaching insight:

> Any self-referential system that depends on information feedback can remain stable only while its epistemic fitness $E = (S/N)R$ stays above a critical threshold E_c.

When the generation of noise outpaces the system's verification and integration capacity, epistemic entropy exceeds control bandwidth, and collapse becomes inevitable.
This principle is universal. It applies as readily to molecules, minds, and machines as to markets and nations.
It is the informational analogue of the second law of thermodynamics—an "entropy of meaning" that must be continuously countered by verification work.

Across all domains examined—biological replication, neural coherence, social order, economic stability, and artificial cognition—the same signature appears: a power-law rise in hazard as E declines, and a characteristic delay between epistemic deterioration and visible breakdown.
This recurring pattern suggests that collapse is not a random failure of material resources but a lawful outcome of insufficient information hygiene.

The Miulus Law therefore provides both a **diagnostic tool** and a **design principle**.
As a diagnostic, it offers measurable early-warning indicators of instability.
As a design principle, it prescribes the minimum rate of epistemic maintenance required for sustainable complexity.
Any civilisation, institution, or intelligence seeking longevity must allocate sufficient energy, computation, and social coordination to keep $E \geq E_c$.

In practical terms, this means investing in open provenance, distributed verification, and interpretive transparency—functions embodied in the proposed *Epistemic Librarian* architecture.

The implications are profound.
Civilisation's survival is not limited by energy or material scarcity, but by coherence—the ability to maintain truthful feedback about reality.
If the Great Filter exists, it may therefore be *epistemic*: a universal tendency for intelligent

systems to drown in their own informational noise before mastering the infrastructure of truth.
Overcoming that filter requires recognising verification as a fundamental natural process—an act of entropy management in the informational domain.

In conclusion, the Miulus Law reframes the human project.
Progress is not merely the accumulation of knowledge but the capacity to preserve its integrity as complexity grows.
To persist, every system—from neuron to nation—must balance creation with correction, discovery with discernment.
The equation (E=(S/N)R) is thus more than a formula; it is a boundary condition for existence itself.

Author Contributions

Conceptualization, theoretical derivation, and manuscript preparation: *Lauri V.N.i Korpela*.

Data and Code Availability

All computational methods and synthetic datasets are available via the **Miulus Toolkit** repository (URL / DOI to be assigned upon submission).

Conflict of Interest

The author declares no competing financial or personal interests.

Appendix I: Quantitative Formulation of Epistemic Fitness

1. Epistemic Fitness as a Systemic Invariant

Let any *complex self-referential system* be defined as

$$S = \{I_t, M_t, O_t\}$$

where:

- I_t = incoming information at time *t*
- M_t = internal model or world-representation at *t*
- O_t = outputs (communications, actions, generated data)

Over each recursive cycle, the system updates its model:

$$M_t + 1 = f(M_t, I_t, O_t)$$

The **epistemic fitness** $\left(E_t\right)$ of the system is a measure of how much verifiable information is preserved or increased relative to epistemic entropy introduced through self-reference, simulation, or fabrication.

$$E_t = \frac{\Delta I_{real}}{\Delta I_{synthetic} + \Delta H}$$

Where:

- ΔI_{real}: change in verifiable, reality-grounded information (signal gain)

- $\Delta I_{synthetic}$: change in unverifiable or self-referentially generated data (signal pollution)
- ΔH: epistemic entropy — uncertainty introduced by transformations, compression, or stochasticity.

A system maintains **epistemic homeostasis** when $Ef > 1$.
When $Ef = 1$, it operates at neutral epistemic fitness (truth preservation).
When $Ef < 1$, the system loses more epistemic integrity than it preserves, approaching collapse.

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2. Epistemic Collapse Threshold

Define **epistemic collapse** as the point where the system's epistemic output becomes decorrelated from empirical reality.

Let:

$$C_t = Corr(O_t, R_t)$$

where R_t is the corresponding empirical or observed reality state.

Then:

$$\lim_{t \to n} C_t \Rightarrow Epistemic\ Collapse.$$

In this regime, outputs of the system become indistinguishable from noise.
The system's self-referential loops dominate over sensory or empirical anchoring, i.e. *it begins to believe its own fabrications.*

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3. Law of Epistemic Conservation

For sustainable operation:

$$\frac{dE_f}{dt} \geq 0$$

Meaning that any system—whether neural, social, or artificial—must regulate its feedback loops to prevent net epistemic entropy increase.
Violating this condition leads to informational degeneracy, analogous to thermodynamic heat death.

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4. Empirical and Engineering Interpretations

- **AI Models:**
  E_f can be estimated as the ratio of *verified data used for training* to *hallucinated or unverifiable data generated and re-ingested*.
  Recursive training loops (self-distillation, synthetic data reuse) drive $E_f \downarrow$.

  Provenance systems (Recorder, Vault) push $E_f \uparrow$.

- **Media Ecosystems:**
  E_f ≈ fraction of human-verifiable journalistic output divided by total informational volume (including synthetic or partisan content).
  When the fake-to-real ratio exceeds a critical threshold, societal consensus collapses $\left(C_t \rightarrow 0\right)$.

- **Biological Cognition:**
  E_f reflects accuracy of internal models vs perceptual corrections.

  Hallucination, delusion, and echo-chamber cognition are low-E_f states.

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5. Corollaries

1. **Miulus Stability Condition:**

$$E_f > 1 \Rightarrow S_{stable}$$

$$E_f > 1 \Rightarrow S_{degenerative}$$

2. **Epistemic Fitness Gradient:**
   Systems with higher E_f outcompete others over time because they conserve and propagate more reliable information. This defines an *evolutionary pressure toward truth-preserving architectures.*

3. **Information Warfare Implication:**
   Counter-leaking and high-fidelity noise intentionally drive $E_f < 1$ for target populations by injecting synthetic uncertainty. Defensive epistemic infrastructure (Recorder, Vault, Verifier) restores $E_f \rightarrow 1$.

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6. Analogy to Physical Law

$$E_f \sim \frac{Signal\ Integrity}{Epistemic\ Entropy}$$

Just as the second law of thermodynamics governs energy dispersion, the Miulus Law governs *truth dispersion*: No complex self-referential system can indefinitely sustain itself while exporting epistemic entropy faster than it imports verifiable signal.

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Appendix II: Calibrated Numerical Example (Self-Training Drift → Fitness Collapse)

Setup (anchored to prior results)

We instantiate the law's variables using our definitions $E = (S/N)R$ with a critical threshold $E_c \approx 0.38$ and hazard curvature $\gamma \approx 2.6$. These values come from the Miulus Law empirical fit (1996–2024 panel; best-fit $E_c = 0.38,\ \gamma = 2.6$).

We then simulate an AI system that gradually re-ingests its own synthetic outputs ("self-training"), which our *Epistemic Collapse* paper frames as driving the **Authenticity Ratio** toward zero as synthetic media scales faster than authentic capture.

Interpretation.

- S_t: share of verified/grounded signal retained at step (t)
- N_t: accumulated epistemic noise (unverified/synthetic mass)
- R_t: reach of verification (fraction of pipeline decisions anchored to verified signal)
- $E_t = (S_t/N_t)R_t$ with collapse when $E_t < E_c$.

Parameterization

Initial conditions reflect a high-quality launch state before drift:

- $S_0 = 0.80,\ N_0 = 0.20,\ R_0 = 0.90 \rightarrow E_0 = (0.80/0.20) \cdot 0.90 = 3.60$ (stable).

At each iteration t, a fraction q_t of the new training mix is synthetic; verification reach lags by $\Delta R = 0.03$ per step; we add a small irreducible entropy term $\eta = 0.02$ (compression/transform loss). Update rules (simple, conservative):

$$S_{t+1} = \left(1 - q_t\right)S_t$$

$$N_{t+1} = N_t + q_t S_t + \eta$$

$$R_{t+1} = R_t - 0.03$$

These dynamics mirror our “verification capacity must grow at least as fast as informational complexity” condition—when it doesn’t, E decays.

Results

We increase synthetic reuse over time to reflect practical pressures (cheap content, faster cycles): $q_1 = 0.20,\ q_2 = 0.30,\ q_3 = 0.40,\ q_4 = 0.50$.

Step	q_t	S_t	N_t	R_t	$E_t = (S/N)R$	**Hazard** $h(E) = \left(E_c/E\right)$
0	–	0.80	0.20	0.90	**3.60**	≈ 0.01
1	0.20	0.64	0.38	0.87	**1.46**	≈ 0.07
2	0.30	0.448	0.592	0.84	**0.64**	≈ 0.30
3	0.40	0.2688	0.7912	0.81	**0.28**	≈ 2.3
4	0.50	0.1344	0.9456	0.78	**0.11**	≈ 24.6

- **Crossing the threshold.** By step 3, $E_3 \approx 0.28 < E_c \approx 0.38$: the system enters the predicted **instability regime**; the hazard metric explodes super-linearly $(\gamma \approx 2.6)$.
- **Mechanism.** Rising synthetic reuse q_t depletes S, swells N, and erodes R as verification coverage lags—exactly the “authenticity ratio collapses toward zero” dynamic formalized for AI-media ecosystems.

Engineering takeaway (ties to Section 7 “Librarian”)

The Librarian/Recorder/Vault stack enforces the compensating inequality $\frac{dV}{dt} \geq \frac{dI}{dt}$ (verification work grows at least as fast as informational complexity), which keeps R high and caps N, driving $\lim_{t \to \infty} E(t) \to 1$ under adequate resources. The simulation above is precisely the failure mode that architecture is designed to prevent.