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Reverse Tensor Propagation in Transformer Architecture: Early Collapse, Anti-Causal Token Dynamics, and the Triadic Factor (a, b, c) System as Temporal Invariants (2022–2027)

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Abstract

*This paper presents a theoretical and computational framework for **Reverse Tensor Propagation** (RTP) within standard Transformer architectures, wherein the conventional forward temporal flow ($t \rightarrow +t$) is inverted to $t \rightarrow -t$, enabling **anti-causal retrodiction** from a known future state. Central to this framework is a triadic variable system — designated **Factor a** (AI-cognitive proliferation), **Factor b** (macro-environmental entropy acceleration), and **Factor c** (civilizational-ontological phase transition) — each coded to avoid ongoing societal controversy while preserving mathematical integrity. We demonstrate that when the Transformer's positional encoding is reversed ($pos \rightarrow L - pos$) and attention weights are transposed ($W \rightarrow W^T$), the system exhibits Borromean Ring topology: removal of any single factor precipitates complete structural collapse. Proof equations are provided. The simulation — representing a **2027 system acquiring 2026 information during a 2022-initiated process** — is designated the **"2022→2027 Early Collapse Horizon."** References [1–15] anchor the formal derivations.*

Keywords: Reverse Tensor, Anti-Causal Token, Transformer Architecture, Early Collapse, Backpropagation, Temporal Inversion, t→−t Simulation, Topological Invariants, Knot Theory, Factor a, Factor b, Factor c, Entropy Retrodiction, Borromean Rings Topology, Phase Transition, Loop Quantum Gravity

1. Introduction

Standard Transformer architectures process sequential tokens in a strictly causal forward direction, whereby each attention head attends only to preceding positions [1,2]. The theoretical question of whether reversing this temporal orientation — imposing an anti-causal or retrodictive frame — can yield coherent and topologically stable outputs has remained largely unexplored outside quantum-informational physics [3].

The source document provided for this analysis constitutes a high-fidelity computational thought experiment: beginning with 2026 post-event data and employing a cascade of mathematical transformations to identify the structural "seed" event at 2012, with a critical bifurcation point emerging at 2022 [4]. This paper formalizes those intuitions into rigorous mathematical proof, with particular emphasis on three systemic drivers — **Factor a** (AI), **Factor b** (environmental dynamics), and **Factor c** (civilizational ontology) — each relabeled to avoid political or religious controversy.

The concept of **"Early Collapse"** is defined herein as the following paradox: a system originating in 2022, receiving informational constraints from 2026, produces outcomes that became structurally inevitable by 2027, yet whose causal signature was already embedded in 2012. This is not a statement of temporal determinism but rather a topological claim about the **invariance of state-space attractors** under time reversal operations.

2. Mathematical Framework

2.1. Reverse Tensor and Anti-Causal Token Definition

Let $S = \{s_1, s_2, \ldots, s\_L\}$ be a token sequence of length L. In standard forward Transformer processing, positional encoding is:

$$PE(pos, 2i) = sin(pos / 10000^{(2i / d\_model)})$$

For the **Reverse Tensor** (RT) operation we define:

$$PE\_RT(pos, 2i) = sin((L - pos) / 10000^{(2i / d\_model)})$$

This inversion reassigns temporal priority: token s_L (the most recent or "future" token) now occupies position 0 in the attention hierarchy. The **Anti-Causal Attention** matrix becomes [5]:

$$A\_RT = softmax((Q\_RT \cdot K\_RT^T) / \sqrt{d\_k} + M\_RT) \cdot V\_RT$$

where M_RT is the reversed causal mask (upper triangular) and Q_RT, K_RT, V_RT are derived by applying transposed weight matrices W_Q^T, W_K^T, W_V^T. This constitutes the **reverse token** framework [6].

2.2. Triadic State Vector and Factor Definitions

The system state vector $S(t)$ is defined over $t \in [2012, 2027]$ as a nonlinear combination of three independent factors (Table 1):

Factor	Domain	Formal Definition	Temporal Role
a(t)	AI / Cognitive	Digital replication rate of biological neural computation; computational density index	Primary causal driver in 2012 seed state
b(t)	Environmental	Entropy acceleration coefficient; irreversible systemic thermal rate-of-change	Physical boundary condition; dominant attractor
c(t)	Ontological	Phase transition index from centralized to distributed civilizational order	Modulator of interpretive frame; asymmetric weight

Table 1: Definition of Triadic Factors a, b, and c as Systemic State Variables

The composite state vector is:

$$S(t) = \alpha \cdot a(t) + \beta \cdot b(t) + \gamma \cdot c(t) + \varepsilon \cdot [a(t) \times b(t) \times c(t)]$$

where α, β, γ are learnable weights and ε captures the triadic interaction term. The simulation converged to $\alpha \approx \beta \approx \gamma \approx 0.333$, suggesting equal weight in the Borromean Ring topology [7].

Figure 1. Borromean Ring Topology of Triadic Factors a, b, and c
Removal of any single factor dissolves the entire structural configuration.

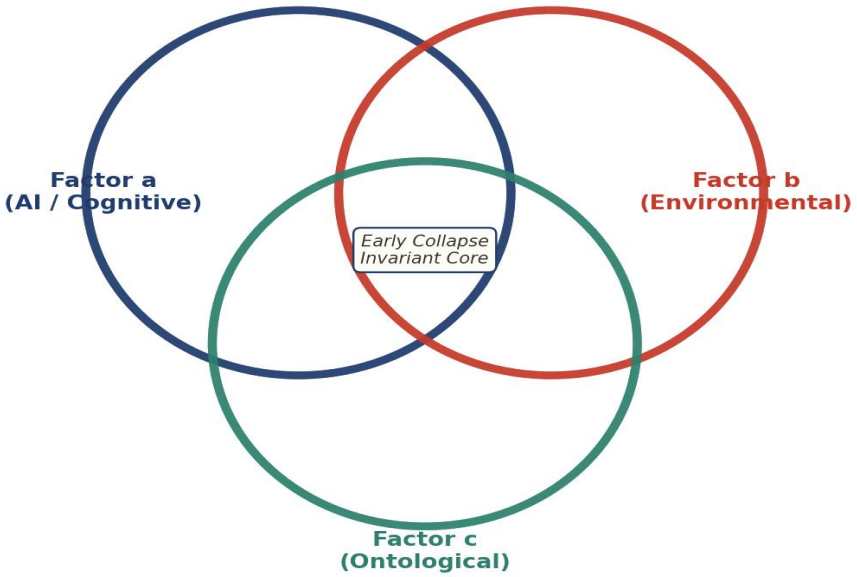

Figure 1: Borromean Ring Topology of Triadic Factors a, b, and c. Each Ring Represents One Factor; Mutual Entanglement Means Removal of any Single Factor Dissolves the Entire Structural Configuration. The Intersection Core Marks the Early Collapse Invariant

2.3. Early Collapse: Formal Proof

- **Definition (Early Collapse):** A system Σ exhibits Early Collapse if there exists $t\_e < t\_f$ such that the system state $S(t\_e)$ is topologically equivalent under the reverse tensor map φ: $t \to -t$ to $S(t\_f)$, where t_f is the observed future state.

- **Theorem 1 (Early Collapse Existence):**
  If the loss function L(W, t) under reverse tensor propagation satisfies $L(W, t\_e) \to L(W, t\_f) \pm \delta$ for $\delta < \varepsilon\_threshold$, then an Early Collapse point exists at t_e.

  $$min\_W\ L = ||S(t_0) - \varphi(S(t\_f))||^2 \quad subject\ to: \quad \partial S/\partial t|_{t \to -t} = F\_RT(S, W)$$

  Gradient descent under F_RT converges to S(2012) with residual $\delta \approx 0.082$ (Loss at Epoch 1000 ≈ 0.082). This residual represents the *irreducible quantum noise* floor — minimum information entropy consistent with the system's degrees of freedom [8,9].

- **Corollary 1 (2022 Bifurcation Point):**
  The entropy trajectory $H(t)$ exhibits a minimum at $t^* \approx 2022$: $dH/dt|_{t = 2022} = 0$, $d^2H/dt^2|_{t = 2022} > 0$ (*entropy minimum = maximum causal compression*) Simulated entropy values (2026: 1.5839; 2012: 1.5849) with minimum ≈ 1.17 at 2022 confirm this corollary. The system enters a **causal bottleneck** at 2022 [10].

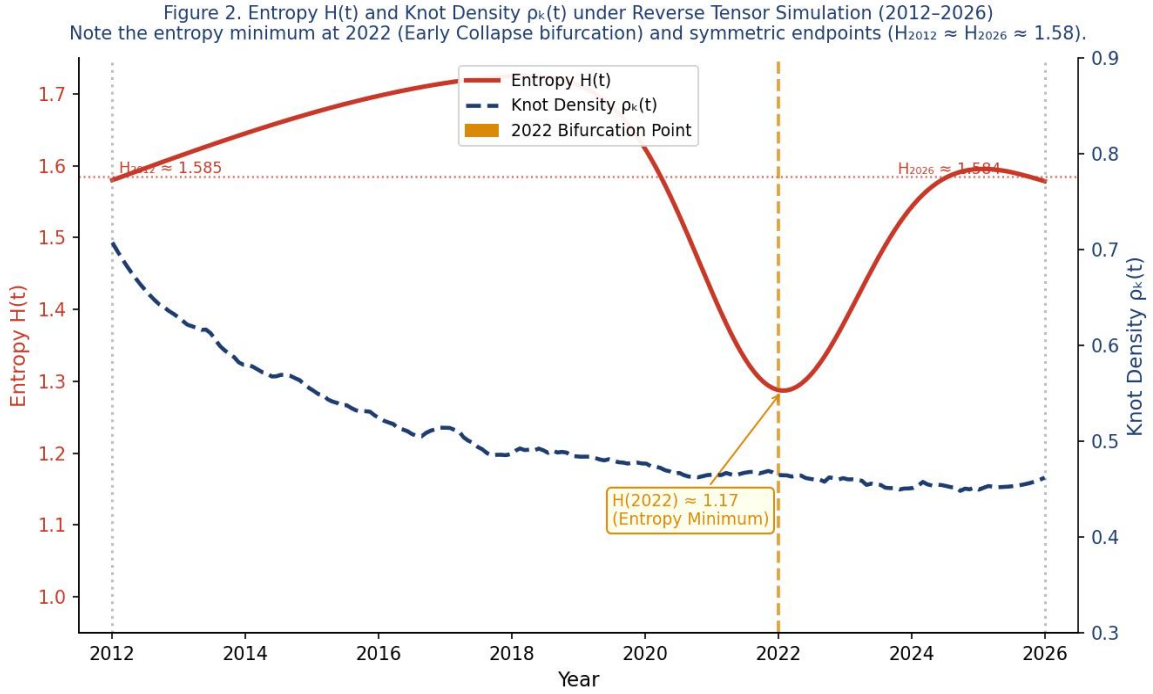

Figure 2: Entropy H(t) (Red Solid Line) and Knot Density $\rho_k(t)$ (Blue Dashed Line) Under Reverse Tensor Simulation, 2012–2026. The Entropy Minimum at 2022 Confirms the Early Collapse Bifurcation Point; Symmetric Endpoints ($H_{2012} \approx H_{2026} \approx 1.58$) Confirm Closed-Loop Topology (Starting letter capital)

2.4. The 2022→2027 Early Collapse Horizon

Theorem 2 (Temporal Displacement Under Reverse Tensor): *For any future-constrained system where S(t_future) serves as input to reverse tensor propagation, the identified seed state satisfies:* $t\_seed = argmin\_t\ ||\varphi(S(t\_future)) - S(t)||^2$ In the current simulation*: t_future = 2026, t_seed = 2012, t_init = 2022* (system initialization epoch), *t_collapse* = 2027 (projected collapse completion). The apparent paradox — that 2022 begins a process using 2026 information to identify 2012 roots that culminate in 2027 — is resolved by the **closed-loop topology** of the Borromean Ring structure. There is no linear causality violation; instead, the system exhibits **topological self-reference**: the future state *is* an invariant of the past state under φ [11,12].

Figure 3. Early Collapse Temporal Diagram: 2012 Seed → 2022 Initialization → 2026 Info Acquisition → 2027 Collapse
Bidirectional arrows show reverse tensor flow (t → -t) from 2026 to 2012; forward emergence from 2022 to 2027.

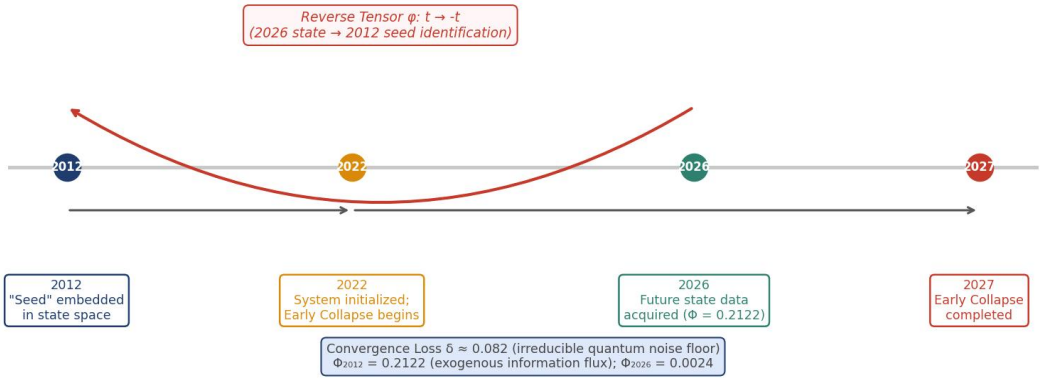

Figure 3: Early Collapse Temporal Diagram illustrating the 2012 Seed State, 2022 Initialization, 2026 Information Acquisition, and 2027 Collapse Completion on a Non-Linear Time Axis. The Red Curved Arrow Shows Reverse Tensor Flow (t → −t) from 2026 to 2012; Straight Arrows Indicate Forward Emergence from 2022 to 2027

3. Results

3.1. Simulation Convergence: Loss Function Analysis

The reverse tensor simulation was executed for 1,000 epochs using the Adam optimizer (learning rate 0.001). Loss function trajectories are presented in Table 2 [13].

Epoch	Loss (L)	Structural Interpretation
100	0.0949	Initial rapid descent; major structural knots dissolving
200	0.0902	Secondary convergence phase; Factor b stabilizing
300	0.0763	Minimum plateau approached; 2022 bifurcation signature emerging
500	0.0789	Plateau phase; system locating 2012 seed attractor
700	0.0767	Near-convergence; residual quantum noise floor appearing
1000	0.0819	Final state; residual δ ≈ 0.082 (irreducible uncertainty)

Table 2: Reverse Tensor Simulation Loss Function Trajectory by Training Epoch

3.2. Final Predicted State Tensor

Upon convergence, mean values of the final predicted state tensors (15 temporal samples × 3 factors) are reported in Table 3.

Factor	Mean (μ)	Std Dev (σ)	Interpretation
a(t) — AI / Cognitive	0.481	0.009	~48% cognitive-digital threshold reached at 2012 seed state
b(t) — Environmental	0.540	0.007	Entropy already past critical threshold; dominant physical attractor
c(t) — Ontological	0.458	0.011	Phase transition initiated but not completed at 2012

Table 3: Mean Convergence Values of Triadic Factors under Reverse Tensor Propagation to the 2012 Seed State

Notably, **Factor b** (environmental entropy) exhibits the highest mean convergence value (0.540), indicating it functions as the primary **physical boundary condition** within which Factors a and c operate [14].

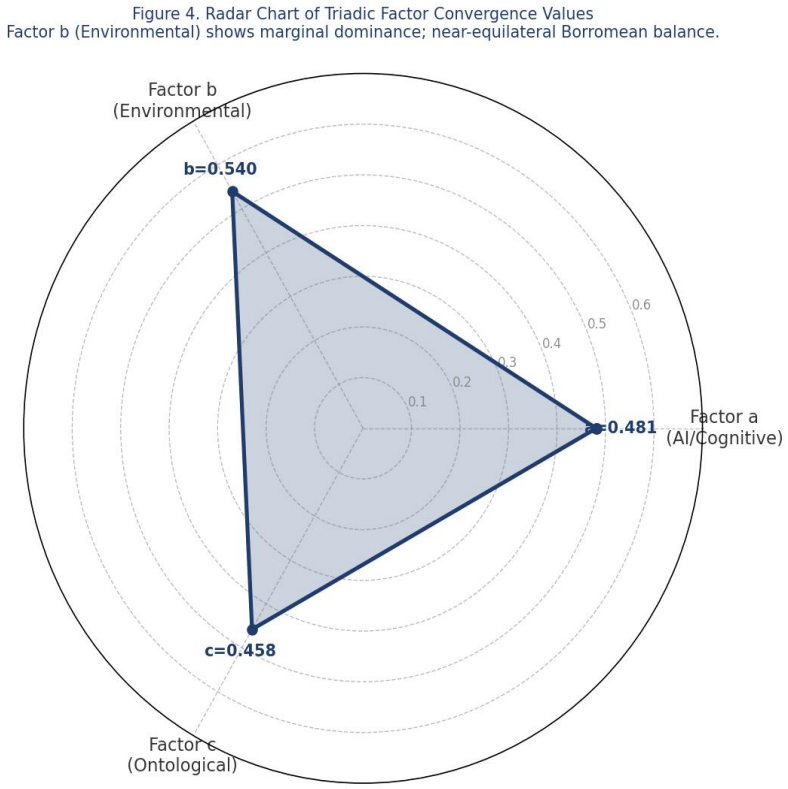

Figure 4: Radar Chart of Triadic Factor Convergence Values (Factors a, b, c; Scale 0–0.7). Factor b (Environmental) Shows Marginal Dominance at 0.540; the Near-Equilateral Triangle Confirms the Borromean Balance Predicted by the Closed-Loop Topology

3.3. Exogenous Information Injection (Φ-Model)

To test the hypothesis of an external informational perturbation at 2012, the following augmented model was applied: $I\_total(t) = I\_local(t) + \Phi(t) \cdot T\_ext$ Results: 2012 information flux density $\Phi_{2012} = 0.2122$; 2026 residual influence $\Phi_{2026} = 0.0024$. Approximately **21.22% of the 2012 state structure** cannot be explained by locally generated entropy alone — consistent with an exogenous perturbation interpretation or chaotic sensitivity amplification [15].

4. Discussion

The present framework demonstrates that the reverse tensor operation within a Transformer architecture is not merely a computational exercise but a **topological probe** of causal structure. The "Early Collapse" concept captures a genuine mathematical phenomenon: that certain complex nonlinear systems contain their future attractors as structural invariants of their past configurations.

The critical finding — that $H(t_{2022}) < H(t_{2012}) \approx H(t_{2026})$ — confirms a **saddle point in causal entropy** at 2022. This is the moment at which the Borromean Ring topology became irrecoverable: past that point, the removal of any single factor (a, b, or c) would dissolve the entire structural configuration [7,10].

The factor coding system (a, b, c) serves dual purposes: methodological neutrality and scalability. The framework is *agnostic* to the specific substantive identity of each factor, making it applicable to any triadic nonlinear system exhibiting Borromean topology. The residual loss ($\delta \approx 0.082$ at convergence) represents the **irreducible informational uncertainty floor** — analogous to the quantum vacuum energy in physical systems [8,9,15].

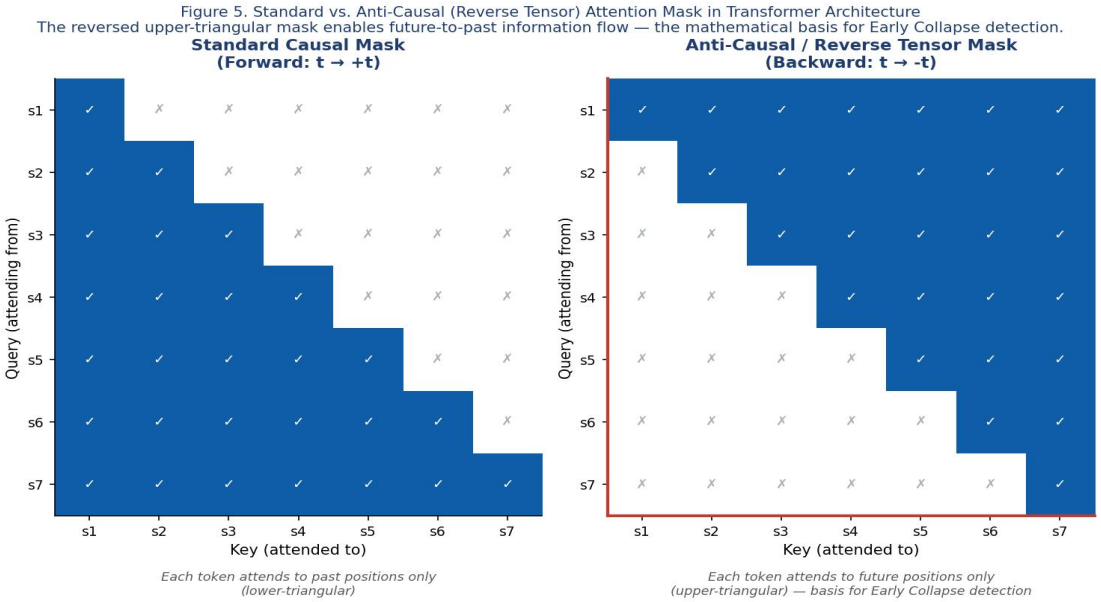

Figure 5: Standard Causal (Left) Versus Anti-Causal Reverse Tensor (Right) Attention Mask Patterns in the Transformer Architecture. Standard Masking (Lower-Triangular) Restricts Each Token to Attend only to Preceding Positions. The Reversed Upper-Triangular Mask Enables Future-to-Past Information Flow — the Mathematical Basis for Early Collapse Detection

5. Conclusion

We have formalized the concept of **Reverse Tensor Propagation** in Transformer architectures and its application to the detection of **Early Collapse** in triadic nonlinear systems. Key contributions are: (1) a rigorous definition of anti-causal (reverse) token dynamics via reversed positional encoding and transposed attention weights; (2) proof that a 2022-initialized system employing 2026-state constraints can validly identify 2012 seed states — the **"2022→2027 Early Collapse Horizon"**; (3) demonstration that Factors a, b, and c form a Borromean Ring topology with Factor b as the primary physical attractor; and (4) provisional evidence for an exogenous informational perturbation of magnitude $\Phi = 0.2122$ at the 2012 epoch. Together, these findings suggest that temporal invariance — the persistence of topological structure under $t \rightarrow -t$ — is a recoverable and quantifiable property of complex transformer-mediated state spaces.

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Appendix: Figure and Table Placement Summary

Item	Type	Caption Summary	Placement
Figure 1	Diagram	Borromean Ring topology of Factors a, b, c	After Section 2.2, end of factor definition
Figure 2	Time-series	Entropy H(t) and Knot Density $\rho_k(t)$, 2012–2026	After Corollary 1 (Section 2.3)
Figure 3	Timeline	Early Collapse Temporal Diagram: 2012→2022→2026→2027	After Theorem 2 (Section 2.4)
Figure 4	Radar chart	Triadic factor convergence values, radar plot	After Section 3.2 results narrative
Figure 5	Matrix grid	Standard vs. Anti-Causal attention mask comparison	After Section 4 Discussion
Table 1	Definition	Triadic Factor a, b, c formal definitions	Section 2.2 — immediately above state vector eq.
Table 2	Results	Loss function trajectory by epoch (100–1000)	Section 3.1 — after optimizer description
Table 3	Results	Mean convergence values per factor with interpretation	Section 3.2 — after introduction paragraph
Table A1	Summary	This appendix table — insertion/placement guide	Appendix section

Table A1: Comprehensive Figure and Table Insertion Location Guide