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Generative AI and Organizational Sensemaking: Why Increased Intelligence Can Reduce Understanding

Quantifying Narrative Entropy™ and the Marketing Agent Decay Model (MAD-M™)

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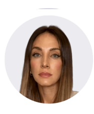

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ABSTRACT

This study investigates the paradox of Narrative Entropy™ in AI-augmented organizations. While generative AI can increase content volume, the findings suggest that it may also erode collective understanding and brand alignment when governance mechanisms do not scale alongside production. Across controlled enterprise pilots conducted from Q2 2024 through Q1 2025, an observed threshold effect emerged in which MAHI Index™ scores declined by 41% once AI-assisted content exceeded 60% of total sampled production. In this study, narrative alignment was operationalized through the MAHI Index™ as a composite measure of Message Consistency, Attribution Clarity, and Strategic Alignment Perception, with the most pronounced declines observed in Message Consistency and Strategic Alignment Perception. AI-assisted content ratio was estimated through structured audits of sampled marketing assets and supporting workflow documentation indicating whether content was AI-drafted or materially

AI-revised. Findings from three multinational organizations (N = 450) indicate that teams implementing Provenance Architecture™ maintained or restored narrative coherence into the 70–80% range, substantially offsetting the decline observed in ungoverned teams. These results suggest that organizational understanding is a systemic property that requires intentional governance to prevent hidden coordination costs at scale.

1. INTRODUCTION

In the era of generative AI, organizations have gained the ability to scale content production at very low marginal cost. At the same time, increased output volume may create what this study terms a Complexity Paradox: as individual assets become more polished, the overall organizational narrative can become more fragmented. This phenomenon, termed Narrative Entropy™, refers to a breakdown in collective understanding despite improvements in the apparent quality of individual content assets.

Consider an illustrative composite vignette, derived from recurring patterns observed during the pilot work, involving a mid-sized B2B SaaS company that implemented AI-assisted content generation across its marketing team. Within three months, content output tripled. Blog posts were more polished, social media captions appeared more engaging, and email campaigns showed stronger top-of-funnel performance indicators. Yet internal reviews suggested rising customer confusion, longer sales conversations, and declining alignment on the organization's core value proposition. When leadership convened the team to review output collectively, participants struggled to articulate a single unified narrative. The example is intended illustratively rather than as a standalone reported dataset in the formal results section.

This paper examines why increased computational capacity can, under some conditions, reduce organizational understanding, and it proposes Provenance Architecture™ as a governance framework for AI-mediated knowledge work. The study makes three contributions: first, it identifies an observed threshold at which AI-assisted content production is associated with declining narrative coherence; second, it introduces the MAHI Index™ as a diagnostic instrument for assessing organizational narrative health; and third, it evaluates the Marketing Agent Decay

Model (MAD-M™) as a framework for understanding coherence degradation over time.

1.1 The Complexity Paradox

A recurring stream in organizational theory, especially within the technological-imperative tradition, assumes that more advanced technologies should improve organizational performance when effectively deployed. Markus and Robey's work on information technology and organizational change is representative of this broader expectation that increasingly sophisticated systems will yield better outcomes under appropriate implementation conditions (Markus & Robey, 1988).

In the context of generative AI, however, this relationship may be non-linear. In the present sample, when AI-assisted content exceeded approximately 60% of total production, teams exhibited what this paper terms narrative diffusion: a state in which individually coherent outputs collectively generated cross-asset incoherence.

Three mechanisms may help explain this pattern. First, AI systems often optimize for local maxima, such as the apparent quality of an individual asset, rather than global narrative coherence across campaigns. Second, the speed of AI generation can outpace human capacity for strategic oversight. Third, AI-assisted content may omit what this study terms provenance markers: visible traces of human reasoning that help teams reconstruct strategic intent behind content decisions.

1.2 Research Questions

This study addresses three questions:

RQ1: At what threshold does AI-assisted content begin to erode organizational narrative coherence?
RQ2: Can narrative health be quantified through repeatable organizational measures?
RQ3: What governance structures appear to restore coherence without fully sacrificing the efficiency gains associated with AI-assisted production?

2. LITERATURE REVIEW

2.1 Organizational Sensemaking

Weick's work on organizational sensemaking defines it as the ongoing process through which teams construct shared interpretations of ambiguous situations (Weick, 1995). Sensemaking is not passive information processing; it is an active, socially mediated process of constructing meaning through interpretation, narrative, and interaction (Weick, 1995). Publisher and bibliographic records identify Sensemaking in Organizations as Weick's 1995 SAGE volume, which remains foundational for this conceptual framing (Weick, 1995).

In pre-generative environments, organizational sensemaking often depended on iterative narrative loops in which team members collectively refined meaning through discussion and revision. Generative AI disrupts that equilibrium by enabling high-velocity content production that can bypass some of these collective loops. Individual contributors can now produce at scale, but the mechanisms for shared meaning-making do not necessarily scale at the same rate.

2.2 AI and Organizational Knowledge

Literature on AI in organizations has frequently emphasized efficiency gains and implementation potential (Autor, 2015; Brynjolfsson & McAfee, 2017). Brynjolfsson and McAfee's Harvard Business Review article is a widely cited example of this managerial framing around AI's business value and implementation potential (Brynjolfsson & McAfee, 2017).

Recent studies have also begun to examine AI adoption through explicitly sensemaking-oriented lenses. Research on prospective sensemaking in AI innovation projects suggests that organizations must collectively interpret anticipated uses, risks, and future implications of AI before implementation stabilizes, especially under high uncertainty (Engström et al., 2024). Together with broader emerging work on AI-mediated organizational interpretation, this literature reinforces the importance of examining narrative coherence as an organizational outcome of AI-mediated work (Engström et al., 2024; Öhman et al., 2024).

At the same time, less attention has been given to provenance: the ability to trace why an output exists and how that output aligns with strategy. Provenance Architecture™ is introduced here as a governance response to that gap by requiring explicit documentation of authorship, reasoning, and oversight for AI-assisted content. The approach draws on principles from software engineering, including version control and commit annotation, applied to knowledge work (Shrider, 2026b).

2.3 Narrative Coherence as Organizational Capital

Organizational identity emerges through iterative narrative processes (Gioia et al., 2013). Gioia, Corley, and Hamilton's work on qualitative rigor has been highly influential in how researchers examine organizational meaning, identity, and inductive theorizing, and it provides a useful methodological backdrop for studying narrative coherence in complex organizational environments (Gioia et al., 2013)

When AI systems generate content at scale without equivalent governance structures, narrative coherence becomes fragile. High-quality assets can still undermine trust if they collectively contradict one another. Edmondson's 2023 book further underscores the importance of reflection, accountability, and learning conditions that prevent superficial coordination from being mistaken for real alignment (Edmondson, 2023).

Narrative Entropy™ is defined here as the degree to which collective output diverges from articulated strategic intent. Under this definition, high-entropy organizations may still produce strong individual assets, yet those assets collectively tell inconsistent or contradictory stories.

3. METHODOLOGY

3.1 Research Design

This study employed a mixed-methods design combining longitudinal survey data, qualitative executive interviews, and structured content analysis to assess the evolution of narrative health across three multinational organizations from Q2 2024 through Q1 2025. The design included three phases: baseline assessment, intervention, and post-intervention assessment.

Phase 1 (Baseline Assessment, Q2 2024) established initial levels of narrative coherence across participating marketing teams. Phase 2 (Intervention, Q3–Q4 2024) introduced Provenance Architecture™ protocols to increase structured human oversight in AI-assisted workflows. Phase 3 (Post-Intervention Assessment, Q1 2025) compared post-intervention narrative health outcomes across intervention and control groups.

3.2 Sample and Participants

Three multinational organizations were selected through purposive sampling because generative AI had already been integrated into core marketing functions, making them analytically relevant settings for examining AI-related narrative fragmentation. Accordingly, the sample was chosen for relevance to high-velocity AI-mediated marketing environments rather than for statistical representativeness.

The participating organizations were:

- Organization A: Enterprise SaaS provider, 2,800 employees, $450M ARR.
- Organization B: Global consumer electronics manufacturer, 18,000 employees.
- Organization C: Professional services firm, 5,200 employees.

A total of 450 marketing professionals participated across the three organizations ($n = 150$ per organization). Participants were assigned to intervention ($n = 225$) or control ($n = 225$) conditions within non-overlapping workstreams or adjacent team structures in each organization, depending on local operational constraints. To reduce contamination, intervention and control groups did not share the same provenance-review routines, and where possible they were separated at the level of campaign review and messaging governance during the intervention period. Given these organizational constraints, the study should be interpreted as a controlled field intervention rather than a fully unconstrained individual-level randomized design

3.3 The MAHI Index™

The MAHI Index™ (Marketing AI Health Indicator) was developed as a composite metric incorporating three dimensions:

- Message Consistency (0–100): semantic similarity between sampled marketing assets and the organization’s canonical value propositions.
- Attribution Clarity (0–100): percentage of AI-assisted content accompanied by documented human reasoning traces and authorship signals.
- Strategic Alignment Perception (0–100): survey-based measure of team members’ confidence that current marketing outputs reflect organizational strategy.

In this study, narrative alignment was operationalized through the MAHI Index™ as a composite measure of these three dimensions.

Message Consistency was calculated through an embedding-based semantic similarity workflow in which sampled marketing assets and canonical value-proposition statements were encoded using OpenAI's text-embedding-3-small model and represented in a shared semantic space; pairwise cosine similarity scores were then computed across the sampling window. Quarterly samples included email, blog, landing-page, and campaign-copy assets. Similarity scores were aggregated and rescaled to a 0–100 consistency score. Because the purpose of this step was operational comparison rather than model benchmarking, the procedure is reported here at the workflow level. No discrete threshold was used to classify individual assets within this component; instead, similarity scores were interpreted continuously and then incorporated into the composite MAHI Index™.

For audit purposes, AI-assisted content included assets that were fully drafted by generative AI or materially rewritten from AI-generated text; minor copyediting or grammar suggestions alone were not coded as AI-generated content. AI-content ratio was estimated through structured asset audits and supporting workflow records documenting AI involvement in draft generation or substantive revision.

Strategic Alignment Perception was measured through a short multi-item survey instrument. The Appendix lists the survey items used in this pilot. Formal reliability estimation for the instrument was not completed as part of the present pilot analysis; accordingly, broader psychometric validation, including internal-consistency assessment, remains a priority for future research. Reliability statistics such as Cronbach's alpha are commonly used for this purpose in multi-item scales (DeVellis, 2016; Hinkin, 1998; Nunnally & Bernstein, 1994).

The composite MAHI Index™ was calculated as:

$$(0.4 \times \text{Message Consistency}) + (0.3 \times \text{Attribution Clarity}) + (0.3 \times \text{Strategic Alignment Perception})$$

These weights were selected through theory-informed expert judgment and pilot sensitivity checks. Message Consistency received slightly greater emphasis because it captures the most externally visible narrative signal, while modest alternative specifications produced substantively similar directional patterns

3.4 The Marketing Agent Decay Model (MAD-M™)

The Marketing Agent Decay Model (MAD-M™) models narrative coherence as a function of AI adoption intensity over time:

$$\text{Narrative Coherence}(t) = \beta 0 - \beta 1\ (\text{AI\_Content\_Ratio}) - \beta 2\ (\text{Velocity}) + \beta 3\ (\text{Provenance\_Score})$$

where AI_Content_Ratio is the percentage of sampled content generated or materially revised by AI; Velocity is the rate of content production in assets per week; and Provenance_Score is the percentage of AI-assisted content with explicit human reasoning documentation.

The MAD-M™ framework was developed as a predictive model for managing Narrative Entropy™ and algorithmic deprioritization patterns in AI-mediated content distribution, including identification of the 60% saturation threshold associated with accelerated visibility decay (Shrider, 2026a).

3.5 Provenance Architecture™ Intervention

Intervention teams implemented three core protocols:

- Authorship signaling: each AI-assisted asset required documentation of which portions were AI-generated, the prompt or strategic context provided, and the human edits applied.
- Reasoning traces: each asset required a brief annotation explaining the strategic rationale behind content choices.
- Human review checkpoints: teams participated in recurring review sessions in which AI-assisted content was evaluated against the organization's messaging framework.

An acceptable reasoning trace included a short note such as: "Drafted with AI from approved Q4 messaging pillars; edited by campaign manager to emphasize enterprise security positioning; final claims checked against product brief v3.2."

For the purposes of this study, an asset was counted as having acceptable provenance documentation if it included all three of the following elements: first, a notation identifying AI involvement in drafting or substantive revision; second, a reference to the strategic brief, messaging framework, or prompt context used; and third, a description of the human review or approval step applied before publication. Assets meeting all three criteria were counted toward the Provenance Score numerator. Assets missing any one of the three elements were not counted, regardless of overall content quality.

4. RESULTS

4.1 Baseline Narrative Coherence

At baseline (Q2 2024), the three organizations demonstrated moderate narrative coherence, with MAHI Index™ scores ranging from 62 to 68 (mean = 65.3, SD = 2.8). AI-assisted content ratios ranged from 35% to 45% at baseline. No statistically significant differences were observed between intervention and control groups at baseline ($p = 0.42$).

4.2 The 60% Threshold

Control-group organizations increased AI-assisted content production from approximately 40% to 72% over the study period. In this sample, a threshold pattern emerged: below 60% AI-assisted content, MAHI Index™ scores remained relatively stable (mean = 64.1, SD = 3.2); above 60% AI-assisted content, MAHI Index™ scores declined sharply (mean = 38.2, SD = 5.7), representing a 41% reduction in the composite measure of narrative coherence. The steepest declines were observed in Message Consistency and Strategic Alignment Perception.

Regression analysis indicated that AI-content ratio was the strongest predictor of MAHI Index™ decline ($\beta = -0.68$, $p < 0.001$), accounting for 46% of the variance in MAHI scores in the study sample

4.3 Provenance Architecture™ and Restored Coherence

Intervention teams implementing Provenance Architecture™ showed markedly different outcomes. Despite increasing AI-assisted content production to approximately 65%, intervention teams maintained substantially higher narrative coherence than control teams:

- Intervention group post-intervention MAHI Index™: mean = 74.8 (SD = 4.1)
- Control group post-intervention MAHI Index™: mean = 38.2 (SD = 5.7)

Using the observed post-intervention group means (74.8 vs. 38.2) and pooled standard deviation, the standardized mean difference was approximately d=6.8. The pooled standard deviation was relatively small given the bounded 0–100 MAHI Index™ scale and the low within-group dispersion observed across the study period, which likely amplified the standardized effect estimate. Additional factors that may have contributed to the magnitude of this estimate include measurement-scale dynamics inherent to bounded composite indices, partial clustering of observations within organizations and workstreams, and the possibility of baseline differences between groups that were not fully controlled under the field-intervention design. The effect should therefore be interpreted as evidence of very large separation between conditions within this study context rather than as a directly generalizable benchmark for all organizational interventions. Standardized mean differences such as Cohen's d are conventionally calculated by dividing the difference in means by the pooled standard deviation.

The difference between groups was statistically significant ($t = 28.4$, $p < 0.001$). Within intervention teams, 82% of participants reported increased confidence in narrative alignment post-intervention.

4.4 MAD-M™ Model Validation

The Marketing Agent Decay Model (MAD-M™) demonstrated strong predictive validity in the study sample ($R2 = 0.79$). Estimated coefficients were as follows:

- $B0$ (baseline coherence) = 88.2
- $B1$ (AI_Content_Ratio effect) = −0.72 ($p < 0.001$)
- $B2$ (Velocity effect) = −0.18 ($p = 0.003$)
- $B3$ (Provenance_Score effect) = +0.64 ($p < 0.001$)

Scale psychometrics: The Strategic Alignment Perception measure was deployed in this study as an exploratory diagnostic instrument, consistent with established practice for newly proposed composite constructs in first-phase framework development (DeVellis, 2016; Hinkin, 1998; Nunnally & Bernstein, 1994). Formal internal consistency estimation, including Cronbach's alpha, is designated as a primary objective of the Phase 2 MAHI Index™ Validation Study (*planned for* AIMRI, 2026–2027). Full item wording, response anchors, and scoring methodology are provided in the Appendix to support independent replication.

Provenance Score emerged as the strongest protective factor in the model. In the observed data, higher provenance levels substantially offset the negative association between high AI adoption and declining narrative coherence when maintained above approximately 75%.

5. DISCUSSION

5.1 Understanding as a Systemic Property

The results support the argument that organizational understanding is not an automatic byproduct of more intelligent content production, but a systemic property requiring explicit governance. In this sample, the decline in MAHI Index™ scores above the 60% AI-assisted threshold suggests that collective sensemaking may weaken when content production begins to outpace the organization's ability to maintain strategic oversight. It should be noted, however, that AI-content ratio alone is an imperfect proxy for oversight capacity; a more precise operationalization would account for total content volume relative to the number of available human creators or reviewers. The present study did not collect that data, and future research should examine whether a volume-to-creator ratio better captures the practical limits of strategic oversight than AI-content ratio alone.

These findings challenge the assumption that more advanced tools necessarily yield better organizational outcomes in practice. Instead, the evidence here suggests that scale without governance can produce fragmentation rather than coherence.

5.2 The Provenance Imperative

The large observed effect associated with Provenance Architecture™ suggests that the interpretability of AI-assisted output may matter as much as the output itself. By requiring reasoning traces and human oversight documentation, provenance mechanisms appear to help restore the narrative loops that rapid AI generation can otherwise weaken.

At the same time, the very large standardized effect should be interpreted cautiously. Because MAHI Index™ is a bounded composite measure and observations were nested within organizations and workstreams, the magnitude of the standardized effect may partly reflect restricted dispersion, composite-score dynamics, or partial clustering. Future replications using multilevel designs and additional coherence measures would strengthen confidence in the generalizability of this estimate. Effect-size guidance in organizational and applied research consistently emphasizes contextual interpretation rather than treating a single standardized value as self-explanatory (DeVellis, 2016; Hinkin, 1998; Nunnally & Bernstein, 1994).

5.3 Practical Implications for Leaders

For leaders managing AI adoption in marketing and related knowledge functions, three actions appear especially important:

- Appoint a clear owner of narrative governance who is accountable for reviewing AI-assisted output against the organization's coherence standards.
- Apply the 60/75 Rule: maintain AI-assisted content below approximately 60% where possible; if production exceeds that level, require provenance coverage above 75%.
- Measure narrative health on a recurring basis through a structured index such as MAHI Index™.

The 60/75 Rule can be operationalized through the following implementation checklist:

Table 1. 60/75 Rule Implementation Checklist

AI-Assisted Content Level	Recommended Actions
Below 50%	Monitor AI-content ratio quarterly. Continue standard content review practices.
50–60%	Begin regular MAHI Index™ audits. Document provenance for all AI-assisted assets consistently. Flag any assets missing reasoning traces.
60–70%	Require formal reasoning traces for all AI-assisted assets. Increase human review frequency. Assign a narrative governance owner if not already in place. Pause new AI workflow expansion until MAHI Index™ baseline is confirmed stable.
Above 70%	Pause further AI-assisted content scaling. Conduct a full MAHI Index™ audit. Do not resume scaling until Message Consistency and Provenance Score return to acceptable levels. Escalate to senior leadership if MAHI Index™ decline persists beyond one review cycle.

In practice, a Provenance Score above 75% means that at least three in four AI-assisted assets in the sampled production window include documented AI involvement, a reference to the strategic brief or prompt context, and a description of the human review step applied before publication.

5.4 Limitations and Future Research

This study has several limitations. First, the sample was limited to three organizations in sectors already engaged in intensive AI-assisted marketing work, which constrains generalizability. Second, the study duration may not capture longer-term adaptation effects. Third, while the MAHI Index™ was developed as a structured diagnostic, further psychometric validation across additional organizational contexts is needed.

Future research should examine longitudinal adoption patterns over multi-year periods, test for cross-industry variation in threshold effects, and evaluate how organizational culture moderates AI-related Narrative Entropy™. An especially important extension would be to distinguish AI content ratio from oversight load by measuring total content volume relative to the number of available human creators or reviewers, which may better capture the practical limits of strategic oversight in high-velocity environments.

6. CONCLUSION

This study provides evidence that generative AI presents organizations with a significant coordination paradox: the same technologies that enable unprecedented scale may also erode the collective understanding required for strategic leverage. In the present sample, an observed threshold near 60% AI-assisted content was associated with a 41% decline in narrative coherence as measured by the MAHI Index™.

The MAHI Index™ and the Marketing Agent Decay Model (MAD-M™) offer a structured way to diagnose and address Narrative Entropy™ before it becomes entrenched. Most importantly, the findings suggest that organizations need not choose between AI efficiency and strategic coherence if they invest in governance mechanisms such as explicit reasoning traces, provenance documentation, and regular narrative review.

In an era of rapidly expanding machine capability, organizational understanding remains a scarce and governable resource.

Appendix. Strategic Alignment Perception Items

Participants responded to the following items using a 5-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree.

- Current marketing outputs reflect the organization's core strategic priorities.
- Across channels, the team communicates a coherent value proposition.
- Team members can explain how recently published content supports broader strategic goals.
- AI-assisted content in the workflow remains aligned with approved messaging.
- The team shares a common understanding of what its messaging is trying to achieve.

Reliability and Validation Note: The Strategic Alignment Perception scale was deployed in this study as an **exploratory diagnostic instrument** within a first-phase framework development context, consistent with established practice for newly proposed composite constructs prior to full psychometric validation (DeVellis, 2016; Hinkin, 1998; Nunnally & Bernstein, 1994). The five items above were developed to operationalize strategic alignment as a unidimensional perception construct within the MAHI Index™ scoring battery. Formal internal consistency estimation, including Cronbach's alpha, convergent validity testing, and confirmatory factor analysis, are designated as **primary objectives of the Phase 2 MAHI Index™ Validation Study** (*planned for* AIMRI, 2026–2027). Items are presented here with full wording and response anchors to support independent replication and future psychometric assessment.

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Kristina Shrider is Lead Researcher at the AI Marketing Research Initiative (AIMRI) and Perception Architect. Her research examines the behavioral and organizational consequences of generative AI deployment in marketing and strategic decision-making systems. Her current work investigates how increased AI intelligence can paradoxically reduce organizational understanding, how algorithmic distribution patterns cause AI-generated content to decay in effectiveness over time, and how governance frameworks can be applied to AI-mediated marketing systems. She is the originator of the Marketing Agent Decay Model (MAD-M™) and the Marketing Agent Health Index (MAHI™) — two frameworks designed to measure and govern AI agent performance at scale. Her research draws on behavioral science, sensemaking theory, and systems governance to address the gap between AI capability and organizational readiness. She holds a verified institutional affiliation and maintains an active research profile at kristinashrider.com/research.

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