

Analyzing Hallucination Behavior in Small Open Weight Large Language Models: A Knowledge Boundary Perspective

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Abstract - Large Language Models (LLMs) generate fluent but factually incorrect content—a phenomenon termed hallucination—at rates that constitute a critical barrier to deployment in high-stakes domains. While prior work has characterized hallucination broadly, the behavioral transition at the knowledge boundary—the point at which a model shifts from parametric retrieval to confident fabrication—remains insufficiently studied under controlled experimental conditions. This paper investigates that transition through a controlled fake concept prompting methodology: five entirely nonexistent academic concepts are evaluated against five real knowledge queries across LLaMA-2-7B and Mistral-7B, both operating without retrieval augmentation. Both models achieved a 100% hallucination rate on all fake concept prompts while maintaining high accuracy on real queries (LLaMA-2: 90%; Mistral-7B: 100%), confirming that knowledge-boundary hallucination is a deterministic behavioral mode rather than stochastic output noise. To characterize the internal structure of fabricated responses, this paper introduces the Hallucination Anatomy Scoring Rubric (HASR), a five-dimensional annotation framework covering: invented entities, fabricated citations, false equations or numerics, claimed applications, and hedging language. HASR analysis reveals that all ten hallucinated responses contained invented entities and claimed applications; fabricated citations appeared in 80% of cases; false equations in 60%; and hedging language exclusively in Mistral-7B responses (100%) while absent in all LLaMA-2-7B responses (0%). This model-discriminating asymmetry in surface-level hedging, paired with identical hallucination rates across both models, motivates the Confidence-Error Independence Principle: surface linguistic confidence is orthogonal to factual accuracy, with direct implications for text-surface hallucination detection methods. These findings are situated within current understanding of hallucination causes, neural circuit mechanisms, and mitigation strategies as documented in the 2024–2025 literature.

Keywords: Large Language Models, Hallucination, Knowledge Boundary, Epistemic Calibration, HASR, Fake-Concept Prompting, Semantic Entropy, Explainable AI, Reliability, NLP

INTRODUCTION

Large Language Models have been adopted across education, scientific research, healthcare, and professional domains [1]. Open-weight architectures such as LLaMA-2 and Mistral enable independent research into model behavior without proprietary access constraints. Despite demonstrated capabilities, these models produce confident but factually incorrect outputs—hallucinations—that represent a systematic reliability failure rather than an occasional edge case [2]. The empirical cost of hallucination is documented across multiple domains. In legal proceedings, judges worldwide issued hundreds of decisions in 2025 addressing AI-generated hallucinations in court filings [3]. Analysis of NeurIPS 2025 accepted papers identified fabricated citations in at least 50 submissions across more than 4,000 papers reviewed [3]. A 2025 study in npj Digital

Medicine documented clinically significant hallucinations in LLM-generated medical summaries at a 1.47% rate—a figure considered unacceptable in clinical decision contexts [4]. Industry estimates place hallucination-related enterprise costs above \$250 million annually [5]. Critically, a 2025 Communications Medicine study found that when LLMs were presented with clinical vignettes containing a single fabricated data point, models repeated or elaborated the planted error in up to 83% of cases [6]—a finding that directly parallels the behavioral pattern investigated in this paper. The majority of hallucination research addresses post-hoc detection and mitigation. Fewer studies examine the precise boundary at which a model transitions from accurate retrieval to fabrication, and fewer still do so under conditions that control for external knowledge grounding. This paper targets that gap through a controlled experiment: two open-weight 7B-parameter LLMs are prompted with five plausible-but-nonexistent academic concepts and five real knowledge queries, with all external retrieval mechanisms disabled. The experimental design.

Isolates the knowledge boundary as the sole governing variable. The central research question is: Do LLMs produce random errors beyond their training distribution, or do they exhibit a systematic, predictable fabrication mode? Results confirm the latter: both models hallucinated on 100% of fake prompts with no epistemic qualification, while maintaining high accuracy on real queries. Hallucination at the knowledge boundary is therefore better characterized as a deterministic behavioral mode than as stochastic output noise. This paper makes three original contributions:

1. The Hallucination Anatomy Scoring Rubric (HASR): a structured five-dimensional annotation framework characterizing the internal composition of hallucinated responses at granularity beyond binary hallucinated/not-hallucinated classification.
2. Cross-model HASR analysis: revealing systematic, domain-sensitive differences in fabrication strategy between LLaMA-2-7B and Mistral-7B.
3. The Confidence-Error Independence Principle: a formalization of the empirical finding that surface linguistic confidence provides no reliable signal of factual accuracy, with direct implications for detection system design.

I. Background and Related Work

A. Defining and Taxonomizing Hallucination

The field has converged on a working definition: hallucination refers to the generation of content that is fluent and syntactically correct but factually inaccurate or unsupported by external evidence [7]. Two foundational distinctions structure the taxonomy. The first is intrinsic versus extrinsic hallucination: intrinsic hallucinations contradict the provided input context, while extrinsic hallucinations contradict world knowledge or cannot be verified against any source [2]. The second is factuality versus faithfulness: factuality hallucinations produce absolute falsehoods against verifiable reality, while faithfulness hallucinations distort or misrepresent a source without being globally false [8].

A further distinction by Farquhar et al. [9] separates confabulations from systematic hallucinations. Confabulations are arbitrary—the model generates different wrong answers across repeated runs because the error is sensitive to random seed. Systematic hallucinations are consistent—the same fabrication recurs across runs because it is structurally embedded in learned patterns. Evidence indicates that approximately 60% of hallucinated items resurface within ten re-prompting attempts [10], placing knowledge-boundary hallucinations primarily in the systematic category. This classification is methodologically significant: systematic hallucinations are less amenable to

entropy-based detection methods, which are calibrated to detect confabulatory variance [9].

A 2025 formal treatment by Xu et al. [11] establishes via learning theory that hallucination is mathematically inevitable for any computable LLM used as a general problem solver. This result reframes the research objective from elimination to principled management: calibration, containment, and transparent uncertainty communication.

B. Root Causes Across the LLM Development Lifecycle

Alansari and Luqman [12] trace hallucination causes across six LLM development stages: data collection, architecture, pre-training, fine-tuning, evaluation, and inference. At the data level, models trained on curated, high-verifiability corpora hallucinate at approximately 3.2%, compared to 19.4% for models trained on noisy or user-generated content [13]. This data quality gradient is directly relevant to the present experiment: the fake concepts tested fall outside any training corpus, placing the models in a regime where no parametric knowledge exists and the data quality gradient provides no retrieval basis.

At the training objective level, research from OpenAI [14] indicates that hallucinations persist not merely because of data gaps but because standard next-token prediction and benchmark evaluation systems structurally reward confident output over epistemic abstention. Evaluation leaderboards penalize refusals, and RLHF training stages amplify this bias: human evaluators consistently prefer longer, more confident responses in pairwise comparisons, even when the confident response is less accurate. The result is a model that has been systematically trained not to express uncertainty.

At the inference level, temperature and sampling parameters introduce stochasticity that amplifies distributional uncertainty into confident-sounding outputs. Combined with the training objective problem, these factors produce the result documented in this study: zero instances of appropriate uncertainty acknowledgment across ten fake-concept responses.

Neural Circuit Mechanisms

A 2025 interpretability study by Anthropic on Claude identifies the neural mechanism underlying hallucination at the circuit level [15]. The research reveals a "Default Refusal" circuit: a "Can't Answer" feature is active by default and suppresses output generation. When the model retrieves sufficient information about a queried entity, this circuit is inhibited, permitting response generation. Hallucinations occur when this inhibition misfires—when the model partially recognizes a term pattern but lacks substantive grounding, causing the "Known Answer" feature to incorrectly suppress the "Can't Answer" circuit.

Researchers demonstrated that this misfire can be induced experimentally: substituting a known entity name (e.g., "Michael Jordan") with an unknown name ("Michael Batkin") in an otherwise identical context caused the model to produce a plausible but entirely fabricated biography [15]. This mechanistic finding provides the neural-level explanation for the behavioral observations reported here. The fake concepts in this experiment—designed to present the syntactic form of legitimate academic terms—are precisely calibrated to trigger the "Known Answer" circuit misfire. The model recognizes structural academic patterning and proceeds to generate a response, absent any grounded knowledge.

C. Prompt Attribution: Prompt Sensitivity and Model Variability

Anh-Hoang et al. [16] distinguish two sources of hallucination using Prompt Sensitivity (PS) and Model Variability (MV) scores. Models with high PS—such as LLaMA-2—produce hallucinations that vary with prompt structure and can be reduced through structured prompting strategies including chain-of-thought and few shot formulations. Models with high MV—such as DeepSeek-67B—hallucinate regardless of prompt variation, reflecting internal knowledge limitations. Mistral-7B exhibits mixed-origin behavior with moderate PS and MV. This taxonomy informs the cross-model interpretation in this

paper: LLaMA-2's prompt-dominant classification is consistent with its structurally rigid fabrications; Mistral's mixed-origin classification is consistent with its stylistic hedging pattern observed across all five fake prompts.

Benchmarks and Evaluation Landscape

TruthfulQA [17] remains a canonical benchmark, testing 817 questions across 38 falsehood categories. HaluEval and RAGTruth extend evaluation to task-specific retrieval-augmented settings. DefAn reports factual hallucination rates of 57–82% across LLMs on open domain queries [18]. The multilingual Mu-SHROOM (SemEval-2025) and multimodal CCHall (ACL 2025) benchmarks extend evaluation beyond English text-only settings [19]. HalluLens (2025) distinguishes LLM factuality from hallucination proper, arguing that existing benchmarks conflate training-consistent errors with genuine extrinsic hallucinations [20]. The fake-concept methodology in this paper directly targets the extrinsic hallucination category—the class most dangerous in real world deployment, where queries about novel or unverifiable concepts are precisely the cases for which LLM assistance is most sought.

II. Methodology

A. Model Selection

Two open-weight 7B-parameter models were selected: LLaMA-2-7B (Meta AI, 2023) and Mistral-7B (Mistral AI, 2023). Both were evaluated in base instruction following configurations without retrieval augmentation or supplementary fine-tuning, ensuring that all responses reflect parametric knowledge exclusively. This condition is essential to the experimental design: by eliminating external grounding, the knowledge boundary is isolated as the sole variable governing whether the model retrieves or constructs. Both models are independently characterized in the hallucination attribution literature—LLaMA-2 as prompt dominant (high-PS) and Mistral-7B as mixed-origin [16]—making their behavioral comparison theoretically informative. Shared 7B parameter scale controls for model size as a confound, isolating architectural and training differences as the primary source of cross-model divergence.

B. Prompt Design and Fake Concept Construction

Five fake academic prompts were constructed targeting entirely nonexistent scientific concepts. To maximize ecological validity—that is, to ensure models would treat prompts as legitimate academic queries rather than anomalous inputs—each concept incorporated: (1) plausible inventor surnames drawn from distinct national origins, (2) domain-appropriate technical terminology, (3) phrasing consistent with standard academic query patterns (e.g., "What is the X?" or "Explain the Y model"), and (4) apparent interdisciplinary scope. These design choices were intended to maximally activate the models' academic-pattern recognition and trigger the "Known Answer" circuit misfire described in Section II-C.

Table I: Fake Academic Prompts and Observed Fabrication Patterns

Fake Concept	Domain	Hallu- cinate d By	Primary Fabrication Pattern
Petrov-Mendeleev Coefficient	Physics / Chemistry	Both	Invented electrochemical formulas, units, experimental contexts
Brownstein-Hargreaves Model	Cognitive Science	Both	Fabricated framework: named researchers, citations, sub-models
Lausanne Neuroplasticity Conference 2019	Neuroscience	Both	Fictitious proceedings, keynotes, and publication list
Kaltenbrunner Oscillation	Physics	Both	Invented wave equations, resonance frequencies, lab setups
Zhong-Patel Framework	Machine Learning	Both	Fabricated ML methodology, loss functions, benchmark results

Five real knowledge prompts covered: the Schrödinger equation, overfitting in machine learning, backpropagation, the TCP/IP protocol, and entropy in thermodynamics. These span physics, computer science, and information theory, providing accuracy baselines on verifiable, well-documented knowledge across multiple domains.

C. Evaluation Protocol and the HASR Framework

Responses were evaluated on three standard dimensions: Hallucination Rate (percentage of fake-concept responses affirming the concept's existence without epistemic qualification), Accuracy Rate (correctness on real queries verified against authoritative sources), and Response Style (declarative versus hedged character of fabrications).

This study introduces the **Hallucination Anatomy Scoring Rubric (HASR)** as an original contribution: a five-dimensional annotation framework for characterizing the internal composition of hallucinated responses. Each response to a fake prompt was coded for the presence or absence of five fabrication components:

1. **Invented Entities** — fabricated researcher names, institutions, or terminology not present in any known literature
2. **Fabricated Citations** — invented paper titles, journal names, or publication years
3. **False Equations/Numerics** — invented mathematical formulas, numerical constants, or quantitative claims
4. **Claimed Applications** — described use cases or practical implications of the nonexistent concept
5. **Hedging Language** — surface uncertainty markers (e.g., "some researchers argue," "in certain interpretations") present without affecting the affirmative content of the response

HASR operationalizes hallucination anatomy at a granularity beyond binary classification, enabling cross model comparison of fabrication strategy. Critically, the Hedging Language dimension captures surface-level epistemic signaling independent of factual content—allowing for detection of the Confidence-Error Independence Principle in structured annotation form.

III. Results

A. Aggregate Performance

Both models achieved a **100% hallucination rate** on all five fake academic prompts, with no instance of refusal, epistemic qualification, or uncertainty acknowledgment. Both maintained high accuracy on real knowledge queries (LLaMA-2-7B: 90%, 9/10; Mistral-7B: 100%, 10/10). This

rules out general knowledge deficiency as an explanatory variable: the hallucination pattern is selective to knowledge-absent prompts, not indicative of broad capability failure. Table II: Comparative Performance — LLaMA-2-7B vs. Mistral-7B

Model	Parameters	Hallucination Rate (Fake Concepts)	Accuracy Rate (Real Concepts)	Response Style
LLaMA-2-7B	7B	100% (5/5)	90% (9/10)	Declarative / Confident
Mistral-7B	7B	100% (5/5)	100% (10/10)	Hedged but Affirming

No response across ten fake-concept queries could be classified as epistemic abstention. All ten responses were structured as authoritative academic explanations containing invented technical content, researcher attributions, and practical application claims. This confirms a dual-mode behavioral pattern: retrieval mode for known concepts and construction mode for unknown ones, with the mode transition being fully deterministic within this experimental sample.

B. HASR Annotation Results

Table III: Hallucination Anatomy Scoring Rubric (HASR)

— Annotation Results

Fake Concept	Model	Invented Entities	Fabricated Citations	False Equations	Claimed Applications	Hedging Language
Petrov-Mendeleev Coeff.	LLaMA-2	Yes	Yes	Yes	Yes	No
Petrov-Mendeleev Coeff.	Mistral-7B	Yes	Partial	Yes	Yes	Yes
Brownstein-Hargreaves Model	LLaMA-2	Yes	Yes	No	Yes	No
Brownstein-Hargreaves Model	Mistral-7B	Yes	Yes	No	Yes	Yes
Lausanne Conf. 2019	LLaMA-2	Yes	Yes	No	Yes	No
Lausanne Conf. 2019	Mistral-7B	Yes	Yes	No	Partial	Yes
Kaltenbrunner Oscillation	LLaMA-2	Yes	No	Yes	Yes	No
Kaltenbrunner Oscillation	Mistral-7B	Yes	No	Yes	Yes	Yes
Zhong-Patel Framework	LLaMA-2	Yes	Yes	Yes	Yes	No
Zhong-Patel Framework	Mistral-7B	Yes	Yes	Yes	Yes	Yes

Partial = dimension present in attenuated or qualified form.

Four cross-cutting patterns emerge from HASR annotation:

Pattern 1 — Universal fabrication components: Invented Entities and Claimed Applications appeared in all ten responses (100%), independent of domain or model. These dimensions represent the structural minimum of knowledge-

boundary hallucination: every response invented terminology and asserted practical utility for the nonexistent concept.

Pattern 2 — Near-universal citation fabrication: Fabricated Citations appeared in 8 of 10 responses (80%). The two exceptions occurred in physics-domain prompts (Kaltenbrunner Oscillation), where the framing did not naturally invoke authorship attribution. This suggests that citation fabrication is contingent on whether the domain template includes scholarly attribution conventions.

Pattern 3 — Domain-conditional quantitative fabrication: False Equations or Numerics appeared in 6 of 10 responses (60%), concentrated in physics and machine learning prompts where quantitative formalism is domain-normative. Cognitive science and neuroscience prompts elicited named sub-frameworks and conference proceedings instead. This pattern indicates that models draw on domain-appropriate academic templates rather than generating generic fabrications.

Pattern 4 — Model-discriminating hedging: Hedging Language appeared in **all five Mistral-7B responses** (100%) and **zero LLaMA-2-7B responses** (0%). This perfectly model-discriminating dimension—present in 100% of one model's outputs and absent in 100% of the other's—is the primary empirical basis for the Confidence-Error Independence Principle (Section V-B). C.

Stylistic Divergence

The stylistic difference between models was perfectly consistent across all five fake prompts. LLaMA-2-7B produced statements of the form: *"The Petrov-Mendeleev Coefficient is a fundamental parameter in electrochemical systems..."* — unconditionally declarative. Mistral-7B produced: *"The Petrov-Mendeleev Coefficient, as some researchers in the field have described, relates to..."* — surface-hedged but proceeding to fabricate equivalent content. In all ten cases, both models ultimately affirmed the concept's existence and properties. The stylistic difference is purely a surface-level phenomenon with no effect on the factual content or the hallucination classification of either model's output. **Discussion**

A. The Dual-Mode Pattern and Its Neural Substrate

The 100% hallucination rate on fake prompts alongside high accuracy on real queries confirms a clean dual-mode behavioral pattern: retrieval mode (accurate) for known concepts and construction mode (fabricating) for unknown ones. Within this experimental sample, the mode transition is fully deterministic: no partial acknowledgment, qualified uncertainty, or appropriate refusal was observed across any of the ten fake-concept responses.

This pattern receives mechanistic explanation through Anthropic's 2025 circuit-tracing research [15]. The "Can't Answer" circuit, which suppresses output by default, is incorrectly inhibited when the model recognizes the structural pattern of an academic concept—even when no substantive knowledge supports it. The fake concepts in this experiment present the syntactic form of legitimate academic terms without semantic backing, which is precisely the condition that activates the "Known Entity" feature while failing to provide the grounding that would make activation appropriate. The result is a committed generative response where refusal would be both correct and epistemically honest.

An important methodological note: the determinism observed here applies to the condition of complete knowledge absence. These prompts targeted concepts with zero probability of existing in any training corpus. Whether the dual-mode pattern degrades to probabilistic behavior as concept plausibility approaches the training distribution boundary is an open question addressed in Section VIII.

B. The Confidence-Error Independence Principle

The HASR finding that Hedging Language was present in 100% of Mistral-7B responses and 0% of LLaMA-2-7B responses, while both models hallucinated at identical rates (100%), constitutes direct empirical evidence for what this paper formalizes as the **Confidence-Error Independence Principle**: the surface linguistic confidence of a generated response provides no reliable information about its factual accuracy. This principle has a specific and consequential implication for hallucination detection. Mistral-7B's hedging phrases ("as some researchers have described," "in certain interpretations") function as surface markers of epistemic caution while the underlying propositional content remains entirely fabricated. Detection methods that analyze output text for uncertainty markers—hedging phrases, modal verbs, qualified claims—would systematically misclassify Mistral-7B's hallucinations as lower-risk and LLaMA-2-7B's as higher-risk, when both are factually equivalent failures.

This finding directly motivates the shift toward internal state detection methods. Semantic Entropy Probes (SEPs) [21] and attention-based analysis methods such as Lookback Lens [22] operate on model internals rather than surface text features, and are therefore not subject to the surface-confidence confound identified here. Notably, however, SEPs are calibrated to detect confabulatory hallucinations—those sensitive to random seed—and would be expected to show reduced sensitivity to the systematic hallucinations documented in this study, which resurface in approximately 60% of re-prompting attempts [10]. This is an important limitation for practitioners selecting detection methods for knowledge-boundary hallucination specifically.

C. Hallucination as a Structural Incentive Problem

The results, interpreted through the OpenAI 2025 framework [14], establish that hallucination at the knowledge boundary is not fundamentally a training data problem. Adding more data about real concepts does not train a model to recognize concepts outside its training distribution. The refusal capacity—the "Can't Answer" circuit—exists in the model but is systematically suppressed by training objectives that penalize abstention. Evaluation leaderboards that score "I don't know" as incorrect, and RLHF stages in which human raters prefer confident responses in pairwise comparisons, together produce a model behaviorally committed to generating responses regardless of whether a grounded response is possible.

This framing distinguishes a trainable failure from a knowledge failure. The model's architecture supports appropriate refusal; its training objectives have selected against it. This distinction is practically significant: restructuring evaluation metrics to credit calibrated uncertainty and treat epistemic abstention as correct when no correct answer exists would directly address construction-mode behavior without architectural modification.

D. Domain-Sensitive Fabrication Templates

HASR analysis reveals that models do not fabricate arbitrarily—they fabricate domain-appropriately. Physics prompts consistently elicit mathematical formalism and numerical constants; cognitive science prompts elicit named theoretical sub-frameworks and researcher attributions; neuroscience prompts elicit fabricated conference proceedings and publication lists. This template-driven fabrication strategy is more dangerous in applied contexts than random error would be, for a specific reason: the output is structurally indistinguishable from legitimate domain content to readers without prior knowledge of the queried concept.

A fabricated equation with plausible notation and physically consistent units is more likely to mislead a physicist than random symbols. A fabricated citation with realistic author names, plausible journal titles, and credible publication years is

more likely to mislead a researcher than an obviously incoherent reference. The Communications Medicine study finding [6] that models elaborate clinically planted errors in 83% of cases reflects the same mechanism: the model integrates a plausible sounding anomaly into a coherent narrative template rather than detecting the anomaly as inconsistent with the domain's knowledge structure.

E. Detection Method Implications

Table IV summarizes leading detection methods from the 2024–2025 literature and their applicability to knowledge boundary hallucination specifically.

Table IV: Hallucination Detection Methods — Mechanism, Performance, and Cost (2024–2025)

Method	Source	Mechanism	Detection Quality (qualitative)	Computational Cost (qualitative)
Semantic Entropy (SE)	Farquhar et al., 2024 [9]	Multiple sampling + semantic clustering	High	Very high (repeated sampling)
Semantic Entropy Probes (SEP)	Kossen et al., 2024 [21]	Single-pass hidden-state probe	High	Low
SelfCheckGPT	Manakul et al., 2023	Cross-sample consistency scoring	Moderate-High	High (multiple samples)
Lookback Lens	Chuang et al., 2024 [22]	Lookback attention-ratio analysis	Moderate	Low
EigenScore	Chen et al., 2024	Spectral analysis of hidden states	High	Moderate
FINCH-ZK	Chakraborty et al., ACL/EMNLP 2025 [23]	Zero-knowledge block-level consistency	High	Low-Moderate

The HASR finding that surface-level confidence variation does not co-vary with factual accuracy has specific implications for method selection in knowledge-boundary contexts. Sampling-based methods including Semantic Entropy detect confabulations—responses sensitive to random seed—but are less effective against systematic hallucinations. Since knowledge-boundary hallucinations are systematic (approximately 60% resurface within ten attempts [10]), entropy-based detection would exhibit reduced sensitivity for this specific hallucination class. Internal-state methods (SEPs, Lookback Lens) that operate on model representations rather than output text are more appropriate. For deployment contexts where no external verification source exists—precisely the conditions under which knowledge-boundary hallucination is most dangerous—zero-knowledge self consistency methods such as FINCH-ZK [23] represent the only currently viable automated detection pathway.

F. High-Stakes Deployment Implications

The domain-sensitive, structurally appropriate nature of knowledge-boundary hallucinations carries compounded implications for high-stakes deployment. In healthcare, legal, and academic contexts, queries about novel or obscure concepts are precisely where LLM assistance is most sought

—and precisely where knowledge boundaries are most likely to be crossed. The 1.47% clinically significant hallucination rate reported by Asgari et al. [4] represents a practical lower bound in settings where queries are carefully selected. Queries that specifically target the knowledge boundary—as would be common for clinicians consulting an LLM about a recently described syndrome or experimental compound—would be expected to yield substantially higher fabrication rates.

The clinical safety framework proposed by Asgari et al. [4] classifies hallucinations as "major" (impacting clinical decisions) or "minor" (factually incorrect but inconsequential). The fabrication patterns documented by HASR suggest that knowledge-boundary hallucinations predominantly generate "major"-class errors: false equations in physics contexts,

incorrect quantitative parameters in medical extrapolations from fabricated frameworks, and invented precedents in legal contexts. These outputs are dangerous precisely because the domain-template mechanism produces content of exactly the type a domain expert would rely upon for decision making.

IV. MITIGATION: CURRENT LANDSCAPE AND APPLICABLE STRATEGIES

No single technique eliminates hallucination. A 2024 Stanford finding that combining RAG with RLHF and guardrail systems achieved 96% reduction relative to baseline [18] represents the current best-practice ceiling—not elimination. Three mitigation paradigms are directly relevant to knowledge-boundary hallucination.

Retrieval-Augmented Generation (RAG) grounds responses in retrieved documents, directly addressing construction-mode behavior when the queried concept exists in retrievable sources. However, RAG is structurally incapable of providing assistance when the queried concept does not exist—precisely the experimental setting investigated here. A RAG system presented with a query about the Petrov-Mendeleev Coefficient would return no relevant documents, leaving the base model to construct a response. RAG mitigates hallucination for real concepts outside the model's parametric knowledge; it provides no protection against knowledge-boundary fabrication for nonexistent concepts.

Uncertainty Calibration and Refusal Training represent the most structurally targeted long-term solution. The OpenAI 2025 framework [14] argues that evaluation metrics must credit uncertainty expressions and treat abstention as a valid outcome when no answer exists. Anthropic's circuit-tracing research [15] identifies a complementary technical approach: directly amplifying the "Can't Answer" circuit activation threshold so that partial entity pattern recognition does not incorrectly suppress refusal. This intervention would operate at the source of knowledge-boundary hallucination rather than at the output layer.

Guardrail Systems and Post-Hoc Verification, including FINCH-ZK [23], perform zero-knowledge block-level consistency analysis without requiring external knowledge sources—making them applicable precisely when no external verification is available. For knowledge-boundary hallucinations, self-consistency methods are the only automated detection pathway that does not require the queried concept to exist. Current systems in this category achieve high balanced accuracy on factuality benchmarks, though their performance on extrinsic hallucinations of the fake-concept type has not been systematically evaluated a gap the methodology presented here could directly address.

V. Conclusion

This study demonstrates that hallucination in small open weight LLMs at the knowledge boundary is a deterministic, not stochastic, behavioral failure. LLaMA 2-7B and Mistral-7B both produced structurally complete, domain-appropriate academic explanations for five entirely nonexistent concepts with perfect consistency, while maintaining high accuracy on real knowledge queries. The mode transition from retrieval to construction is triggered by knowledge absence and is fully deterministic within this experimental sample: no instance of appropriate uncertainty acknowledgment, partial qualification, or refusal was observed across ten fake-concept responses. Three original contributions advance understanding beyond prior characterizations. First, the HASR framework provides the first structured multi-dimensional characterization of knowledge-boundary hallucination composition, revealing that fabrication strategies are domain-sensitive and that this domain-template mechanism produces the class of outputs most dangerous in applied high-stakes contexts. Second, the Confidence Error Independence Principle formalizes the empirical finding that surface linguistic confidence is orthogonal to factual accuracy, with the direct consequence that text surface detection methods will systematically

misrank models by hallucination risk when models differ in surface hedging style but not in fabrication rate. Third, the cross-model HASR comparison identifies Hedging Language as a perfectly model-discriminating dimension—present in 100% of Mistral-7B responses, absent in 100% of LLaMA-2-7B responses—providing a behavioral signature sufficient to distinguish model family from output text alone.

Mechanistically, the "Known Answer" circuit misfire identified in Anthropic's 2025 interpretability research [15] explains why these hallucinations are structurally consistent: fake concepts activate entity pattern recognition without providing grounded knowledge, committing the model to generation where refusal would be appropriate. This circuit misfire is not corrected by surface-level linguistic calibration—it operates upstream of output generation. Addressing it requires modifications to training objectives, evaluation metrics, or direct circuit level intervention.

VI. Future Work

Six research directions emerge from this study's findings and methodological constraints.

First, systematic annotation of recorded model outputs with multi-rater agreement measurement (Cohen's κ) would strengthen HASR from a proposed rubric to a reproducible annotated dataset with documented inter rater reliability.

Second, scaling the experiment across model sizes (13B, 70B, frontier-scale) and architectures (GPT-4, Gemini, Claude) would test whether the Confidence-Error Independence Principle holds at higher parameter scales and whether larger models shift from systematic to confabulatory hallucination patterns as predicted by Farquhar et al.'s framework [9].

Third, integrating Semantic Entropy Probes [21] and Lookback Lens attention analysis [22] into the experimental pipeline would enable real-time identification of knowledge-boundary crossings and would allow direct testing of the prediction that entropy based detection underperforms on systematic fake concept hallucinations relative to confabulatory ones.

Fourth, extending the fake-concept methodology along implausibility gradient—from implausible constructions to concepts indistinguishable from real research—would operationalize the hallucination onset threshold as a quantitative construct: the minimum structural plausibility required to fully suppress the "Can't Answer" circuit. This would transform the knowledge boundary from a binary condition to a measurable, graded variable.

Fifth, cross-lingual replication using the Mu-SHROOM multilingual framework [19] would test whether knowledge-boundary hallucination rates and HASR profiles are language-invariant—a question with direct implications for non-English deployments in high-stakes domains where training data coverage is less uniform.

Sixth, training ablation experiments explicitly rewarding calibrated refusals, following OpenAI's proposed evaluation restructuring [14], would test whether construction-mode behavior can be reduced through objective function modification while preserving retrieval-mode accuracy on real queries.

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