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The Double-Lock Framework: A Multi-Layered System for Grounded Retrieval-Augmented Generation and Hallucination Mitigation

Maleerat Sodanil
Faculty of Information Technology, King Mongkut's University of Technology North Bangkok, Bangkok, Thailand
maleerat.s@it.kmutnb.ac.th

ABSTRACT

Retrieval-*Augmented Generation (RAG) systems have significantly improved the factual grounding of large language models (LLMs). However, challenges remain in ensuring both semantic correctness and transparent attribution, as models may still produce hallucinated or unverified outputs. This paper proposes the Double-Lock Framework, a multi-layered architecture that integrates data engineering, linguistic attribution modeling, and dual validation mechanisms to mitigate hallucinations. A high-fidelity "Gold Standard" dataset is constructed using strict filtering criteria based on factual consistency and hallucination labels. The framework introduces attribution markers to enhance interpretability and employs both supervised fine-tuning and reward-based optimization for model training. A two-stage validation mechanism combining regex-based linguistic checks and predictive AI scoring ensures both transparency and factual accuracy. Experimental evaluation on a 6,000-sample dataset demonstrates that while regex-based validation alone results in a 7.72% hallucination leakage rate, the proposed Double-Lock mechanism achieves 0% leakage. The framework effectively bridges the gap between retrieval and human-understandable knowledge synthesis, enabling the development of reliable and trustworthy AI systems.*

Keywords: Retrieval-Augmented Generation, Hallucination Mitigation, Linguistic Attribution, Factual Consistency, Natural Language Processing, Explainable AI, RLHF, Knowledge Grounding

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1. Introduction

The evolution of large language models has enabled significant advancements in natural language understanding and generation. Retrieval Augmented Generation (RAG) enhances these capabilities by incorporating external knowledge sources during inference. However, despite improvements in grounding, RAG systems remain susceptible to hallucinations and lack transparent attribution mechanisms.

This paper introduces the *Double-Lock Framework*, designed to ensure that generated responses are both factually accurate and linguistically transparent. By integrating structured data filtering, attribution aware linguistic modeling, and a dual layer validation mechanism, the framework transforms RAG systems into reliable knowledge synthesis tools.

The rapid advancement of large language models (LLMs) has significantly transformed natural language processing, enabling systems to generate highly coherent and contextually relevant text. Despite these capabilities, the credibility of LLMs is frequently undermined by a critical limitation known as *hallucination*, wherein the model produces syntactically fluent yet factually incorrect or unsupported information [1, 2]. This issue arises because LLMs fundamentally operate through statistical pattern recognition rather than genuine semantic understanding. As a result, they predict the most probable sequence of tokens based on training data, often prioritising plausibility over factual correctness [3, 4].

Hallucinations become particularly problematic when models are required to generate precise or domain-specific information, where even minor inaccuracies can lead to significant consequences [5]. Prior research identifies multiple contributing factors, including data noise, model drift, prompt ambiguity, and domain mismatch [6]. More broadly, hallucinations stem from a combination of data quality limitations, the probabilistic nature of autoregressive generation, and insufficient grounding in verifiable knowledge sources [7, 8].

Given the growing deployment of LLMs in high-stakes domains such as healthcare, finance, and scientific research, mitigating hallucinations has become a central research challenge. Existing approaches span data-centric, model-centric, and inference-time strategies, each addressing different aspects of the problem. However, no single method has proven universally effective, highlighting the need for comprehensive and accessible mitigation frameworks.

2. Literature Review

2.1 Foundations of Hallucination and Its Causes

Recent studies have examined the underlying causes of hallucinations from both architectural and cognitive perspectives. Lingyi Meng classified hallucinations into two primary categories: cognitive gaps and statistical biases, emphasizing the inherent limitations in current model architectures [9]. Similarly, C. Gu identified critical shortcomings in existing mitigation approaches, including the lack of standardized evaluation metrics, insufficient diagnostic capabilities, and limited support for domain-specific adaptation [10].

These findings reinforce the notion that hallucinations are not merely incidental errors but are deeply rooted in the design and training paradigms of LLMs. Consequently, effective mitigation requires interventions across

multiple stages of the model lifecycle.

2.2 Prompting and Retrieval-Based Approaches

A widely adopted class of mitigation techniques focuses on improving inference-time behavior without modifying the underlying model. Few-shot prompting strategies guide model outputs by providing contextual examples, thereby reducing ambiguity [11]. Retrieval-Augmented Generation (RAG) integrates external knowledge sources to ground responses in verifiable information, significantly improving factual accuracy [12]. Further advancements include self-reflective prompting loops and retrieval-confidence thresholding, which enable models to assess the reliability of their outputs [13, 14]. Fact-verification tools such as SciFact and PubChecker have also been introduced for post-generation validation to ensure alignment with trusted knowledge sources [15, 16].

2.3 Model Architecture and Multi-Agent Systems

More complex approaches involve architectural modifications and multi-agent systems. For example, Darwish proposed a multi-agent orchestration framework in which multiple LLMs collaboratively generate and verify outputs [17]. While effective, such systems require substantial computational infrastructure, limiting their accessibility.

Similarly, architectural innovations introduced by Yu entail fundamental changes to model design that are often impractical for most practitioners due to limited access to training pipelines [18]. In the context of multimodal systems, large vision-language models have been explored to enhance factual grounding by incorporating attribute-level information [19], although their deployment remains limited.

2.4 Knowledge-Integrated and Decentralized Approaches

Integrating structured knowledge sources has emerged as another promising direction. Guan proposed combining LLMs with knowledge graphs to improve factual consistency [20]. However, the effectiveness of this approach is highly dependent on the completeness and accuracy of the knowledge graph.

Decentralized approaches have also been explored. Moroney introduced a blockchain-based framework that leverages multiple LLM services and consensus mechanisms to assess the reliability of outputs [21-24]. Although conceptually robust, such methods introduce additional system complexity and latency.

2.5 Training Data and Model Editing Techniques

Addressing hallucinations at the data level remains one of the most fundamental strategies. Filtering large-scale datasets to include only high-quality sources, such as Wikipedia and academic publications, has been shown to improve model reliability [25, 26]. Additionally, synthetic data generation, such as textbook-style datasets used in models like phi-1.5, enhances factual grounding and reasoning capabilities [27, 28].

Model editing techniques provide another avenue for mitigation by directly modifying learned knowledge. Methods such as ROME enable targeted updates to specific facts through rank-one parameter adjustments [29]. MEMIT extends this approach to large-scale updates across multiple layers [30] [Meng, K.; Sharma], while GRACE introduces external memory modules to store updated knowledge without altering model parameters [31, 32]. Training-free approaches like In-Context Knowledge Editing (IKE) inject factual corrections during inference. To reduce hallucinations, Ishadya proposed an integrated mitigation framework that combines advanced prompt engineering with knowledge-grounded techniques specifically, Retrieval-

Augmented Generation (RAG) and the Model Context Protocol (MCP) without altering the underlying model parameters. [33] Meanwhile, Kou [34] introduced a unified framework for hallucination mitigation based on a structured three-dimensional taxonomy: mechanism based strategies, phase specific interventions, and cross-phase integrative approaches.

Recent advancements, including IFMET, focus on multi-layer editing to improve consistency across shallow and deep representations. Additionally, iterative verification frameworks such as Chain-of-Verification and retrieval-based validation methods further enhance the reliability of outputs by refining generated responses [35, 36].

2.6 Post-Generation Verification and Uncertainty Estimation

Post-generation verification has gained increasing attention as a practical mitigation strategy. Techniques such as RARR introduce structured research and revision stages to correct unsupported content [37]. Context-aware prompting methods also help detect and resolve self-contradictions within generated text [38].

Uncertainty estimation methods, including Monte Carlo dropout and softmax calibration, provide quantitative measures of model confidence, enabling the identification of unreliable outputs [39, 40]. These techniques, combined with external verification tools, contribute to more robust and trustworthy LLM deployments.

2.7 Summary of Research Gaps

Despite extensive research, several limitations persist. Many advanced techniques require significant computational resources or access to proprietary model architectures, limiting their practical applicability. Furthermore, existing approaches often address isolated aspects of hallucination without providing a unified, scalable solution. The lack of standardized evaluation frameworks and domain-adaptive benchmarks further complicates comparative analysis and real-world deployment.

While prior work addresses hallucination through isolated interventions such as prompting, retrieval, or post-hoc verification, there remains a lack of unified frameworks that integrate data quality, linguistic grounding, and semantic validation. To address this gap, the proposed approach begins with a data-centric foundation, described next

2.8 Data Engineering: Gold Standard Construction

The foundation of the framework is the construction of a high-quality training dataset, referred to as the *Gold Standard corpus*. This dataset ensures that model outputs are strictly aligned with the retrieved context.

3. Testbed

Having established the construction of a high-fidelity dataset and attribution-aware representations, we now present the system-level architecture that integrates these components into a unified pipeline for generation and validation.

Figure 1illustrates the proposed testbed architecture of the Double-Lock Framework, a multi-layered system designed to ensure both factual correctness and linguistic transparency in retrieval-augmented generation.

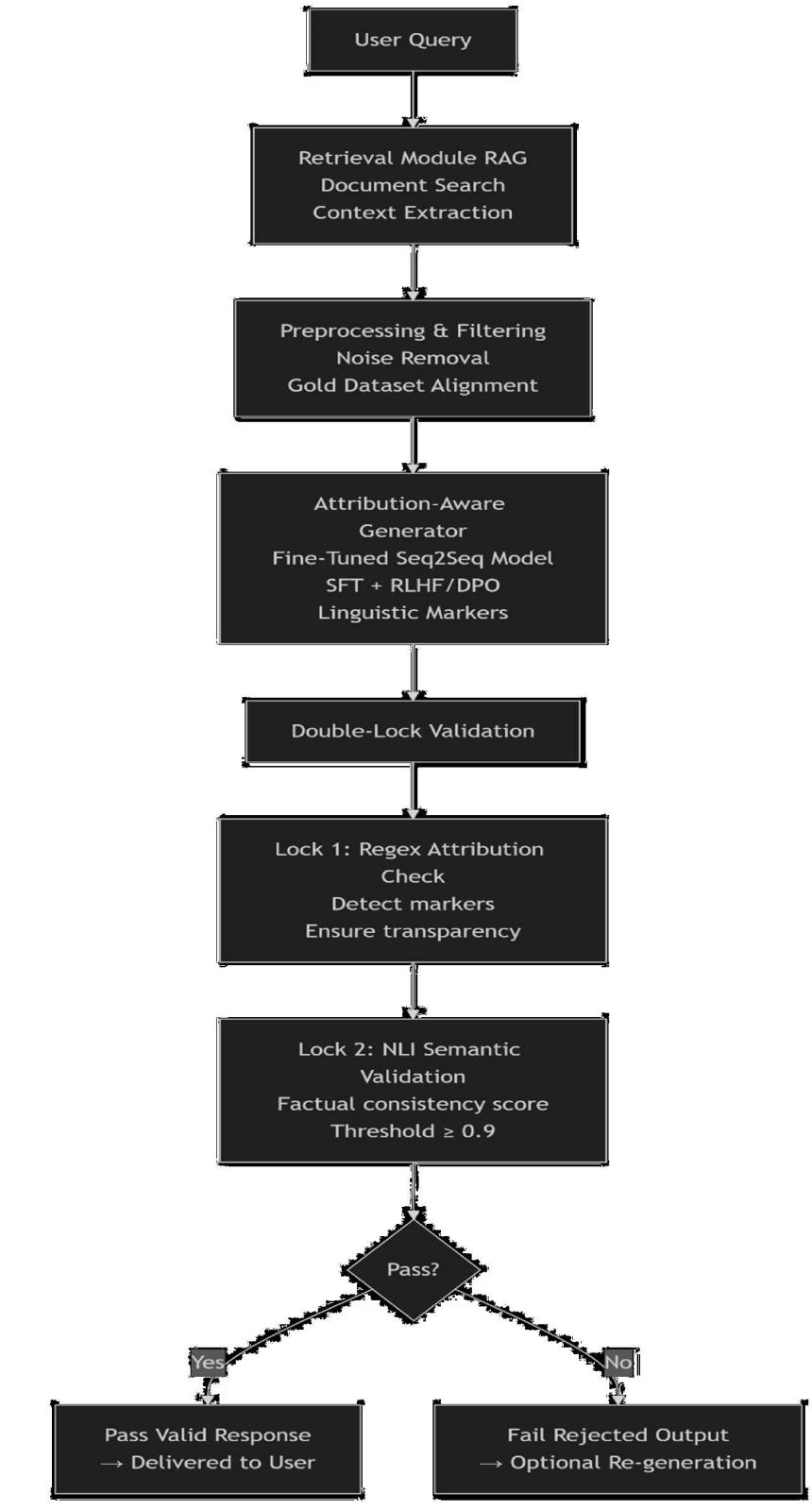

Figure 1. Testbed architecture of the Double-Lock Framework

The pipeline begins with a user query, which is processed by a Retrieval-Augmented Generation (RAG) module to extract relevant contextual information from external knowledge sources. This retrieved context is then passed through a preprocessing and filtering stage, where noise is removed, and alignment with the high-quality *Gold Standard dataset* is enforced.

The processed input is fed into an attribution-aware generative model, trained using supervised fine-tuning and reward-based optimization techniques (RLHF/DPO). This model produces responses enriched with explicit attribution markers, enabling traceability to the source context.

A key contribution of the framework lies in the Double-Lock validation mechanism, which acts as a sequential guardrail system:

• Lock 1 (Regex-Based Validation): Ensures the presence of linguistic attribution markers, enforcing interpretability and preventing ungrounded responses.

• Lock 2 (Semantic Validation via NLI): Evaluates factual consistency between the generated response and the retrieved context, producing a quantitative score. Only responses exceeding a strict threshold (≥0.9) are accepted.

Let a generated response R be accepted only if:

$$V(R) = V_{regex}(R) \wedge V_{semantic}(R)$$

where:

- $V_{regex}(R) = 1,$ if attribution markers are present
- $V_{semantic}(R) = 1$ if $(R, C) \geq \tau$

Responses that pass both validation stages are delivered to the user as verified, grounded outputs, while those that fail are rejected or optionally regenerated.

This testbed demonstrates how integrating data quality control, attribution-aware generation, and dual-layer validation creates a robust pipeline that eliminates hallucination leakage while preserving explainability, making it suitable for high-stakes AI applications.

4. Analysis

Using the above testbed, we begin analysing the data.

4.1 Filtering Criteria

To establish a high-quality training corpus, the dataset is filtered using the following conditions:

- $factual\_consistency\_score > 0.9$
- $hallucination\_label\_with\_rag = 0$

These constraints ensure that only responses that are both factually consistent and free from hallucinations are retained.

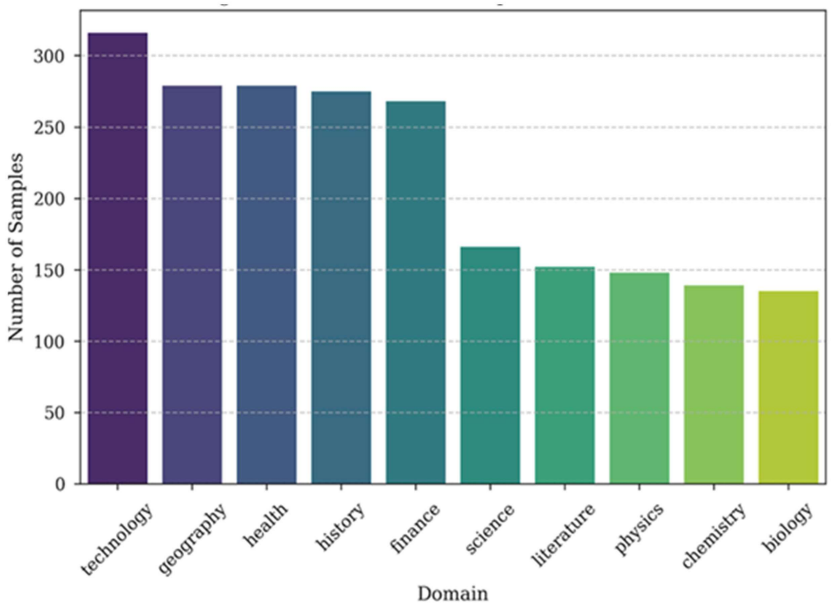

Figure 2. Dataset Distribution: This illustrates the diversity of the high-quality corpus established

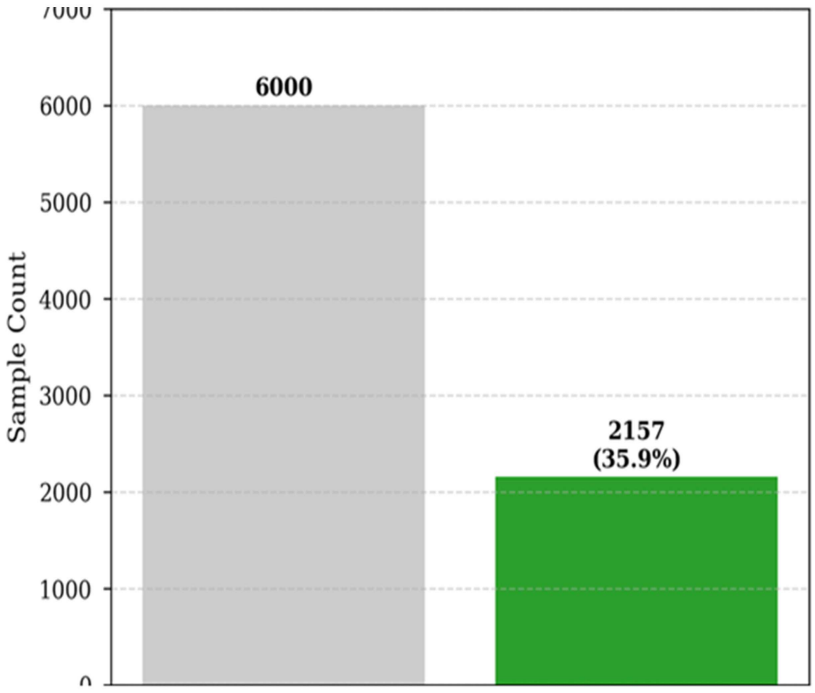

Figure 3. This figure visually supports the point about the difficulty of achieving fully grounded responses by showing how many samples were discarded

Operational Definition of "Hallucination"

Within this framework, a hallucination is defined as any model-generated response that fails to meet one of two distinct criteria:

• Linguistic Hallucination (Attribution Failure): This occurs when a response is factually correct but lacks the required attribution markers (e.g., "According to the retrieved context..." or "Based on the evidence..."). Even if the information is true, the framework classifies it as a "trustworthiness failure" because the model failed to cite its source.

• Semantic Hallucination (Factual Inconsistency): This is a traditional hallucination where the response contains information that is not supported by or contradicts the provided context. The framework identifies these when the *factual_consistency_score* falls below a specific threshold (typically 0.9).

A response is only considered "Hallucination-Free" if it is both attributed (linguistically grounded) and accurate (semantically consistent).

4.2 Dataset Statistics

Metric	Value
Total Samples	6,000
High-Fidelity Samples	2,157
Retention Rate	35.95%

Table 1. Gold Standard Dataset Statistics

The relatively low retention rate highlight.s the inherent difficulty in achieving fully grounded responses, even within RAG pipelines. The filtered subset represents optimal training data for reliable response synthesis. This indicates that nearly two-thirds of raw RAG outputs fail to meet strict grounding criteria, suggesting that naïve RAG pipelines are inherently unreliable without post-filtering

4.21 Training Data

The training data for the framework is a high-fidelity "Gold Standard" corpus derived from an initial 6,000-sample dataset:

• Filtering Process: Samples are only included if they meet two criteria: a *factual_consistency_score* > 0.9 and *a hallucination_label_with_rag* of 0.

• Final Dataset: After filtering, the corpus consists of 2,157 high-fidelity samples (a 35.95% retention rate).

• Format: The data is transformed into an instruction-tuning format where the input is a Context + Question pair, and the target is an "Attributed Response" (e.g., "According to the retrieved context...").

4.22 Failure Modes

The documentation identifies two primary failure modes or limitations, particularly when using individual

validation methods rather than the integrated Double-Lock system:

• False Negatives (Stealthy Hallucinations): This occurs when a response bypasses simple linguistic checks (like regex patterns) but still contains incorrect or hallucinated information. In experimental evaluations, regex-based validation alone allowed 463 hallucinated responses to pass undetected, resulting in a 7.72% leakage rate.

• Transparency vs. Correctness Imbalance: Regex-Only Validation: Improves interpretability but fails to prevent semantic hallucinations entirely.

• Predictive AI Check: Ensures semantic correctness but lacks transparent attribution (users cannot easily trace the origin of information). The response is then analyzed by a Natural Language Inference (NLI) model to compute the *factual_consistency_score*.

• Protocol: The model compares the Response against the Context.

• Leakage Calculation: Leakage is measured by counting how many samples pass the Stage 1 (Regex) check but fail the Stage 2 (Factual Consistency) check.

• False Positives: While identified as a theoretical risk that could block valid responses and affect usability, the Double-Lock framework reported a count of 0 for false positives in its experimental results

4.23 Leakage Measurement Protocol

"Leakage" refers to instances where a hallucinated response bypasses a validation layer and is presented to the user as a "valid" answer. The framework measures this using a comparative protocol:

Stage 1: Regex-Based Validation (Linguistic Check)

The system first scans the output for specific attribution patterns.

• Protocol: If the response contains phrases like "Based on the provided context," it passes this stage.

• Observation: The documentation notes that this stage alone is insufficient because a model can "learn" to use these phrases while still providing incorrect facts (Stealthy Hallucinations).

4.24 Instruction-Tuning Format

The filtered dataset is transformed into an instruction-based format:

• Input: Context + Question

• Target: Attributed Response

Example Transformation:

• Input:

Context: URL stands for Uniform Resource Locator

Question: What does URL stand for?

• Target:

Response: Using the retrieved evidence, Uniform Resource Locator

This structure facilitates effective supervised learning for grounded text generation.

While the Gold Standard dataset ensures high-quality supervision, the model must also learn how to express grounded knowledge explicitly. This motivates the need for linguistic attribution modeling, discussed in the next section.

4.25 Feature Engineering: Linguistic Attribution

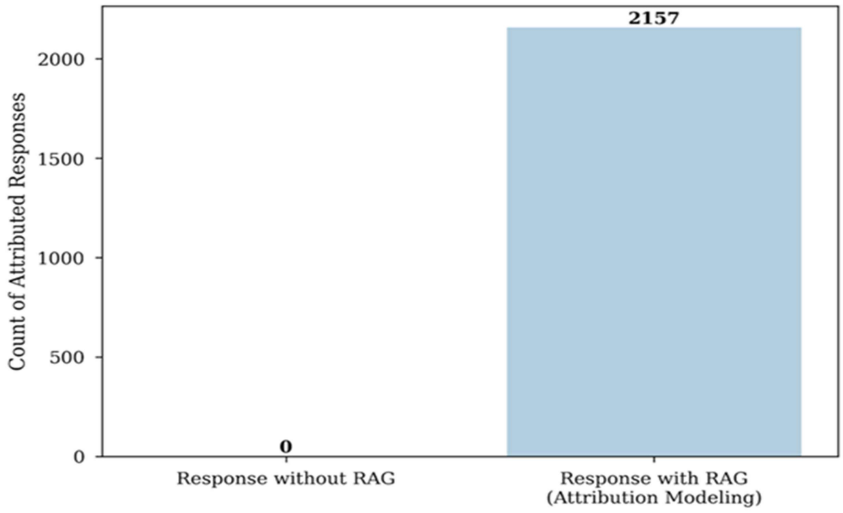

Figure 4. Transformation. This provides empirical evidence that the transformation increases the presence of grounded markers compared to standard RAG

4.3 Attribution Marker Categories

Attribution markers are classified into three categories:

• Explicit Frames: “Based on the provided context…”

• Validation Markers: “The context confirms that…”

• Source Anchors: “Source A indicates…”

4.3.1 Linguistic Transformation

This qualitative shift is supported by improved consistency (Experiment 2), indicating that attribution markers not only improve trust but also stabilize model outputs.

The transformation significantly enhances user trust by explicitly linking responses to their source.

Feature	Assertive Statement	Attributed Statement
Tone	Internal	Relational
Example	Ottawa is the capital of Canada	According to the context, Ottawa is the capital
Trust Level	Low	High

Table 2. Assertive vs Attributed Statements

4.3.2 Additional Enhancements

- Syntactic simplification improves readability
- Anaphora resolution removes ambiguity
- Controlled marker usage avoids redundancy

Once attribution-aware representations are defined, the next step is to integrate these features into the model training process, enabling the system to generate both factually correct and interpretable responses.

Let C denote the retrieved context and R the generated response. The factual consistency score is computed as:

$$f(C, R) = \text{NLI}(C, R) \in [0,1]$$

where values closer to 1 indicate strong entailment.

5. System Workflow

The workflow can be formalized as a sequential transformation pipeline mapping a query-context pair to a validated response through structured intermediate stages. The workflow represents a structured pipeline in which each stage incrementally refines the quality of the generated outputs. Preprocessing removes noise, augmentation enhances robustness, training enables learning of grounded patterns, and validation ensures that only reliable outputs are delivered. This layered design ensures both scalability and reliability in real-world deployments.

1. Preprocessing: Clean the dataset and remove noise

2. Augmentation: Use hallucination types for contrastive learning

3. Training: Apply sequence-to-sequence fine-tuning

4. Validation: Deploy a “Judge Model” for scoring outputs

This pipeline ensures a transition from data retrieval to meaningful knowledge synthesis

5.1 Model Design and Training

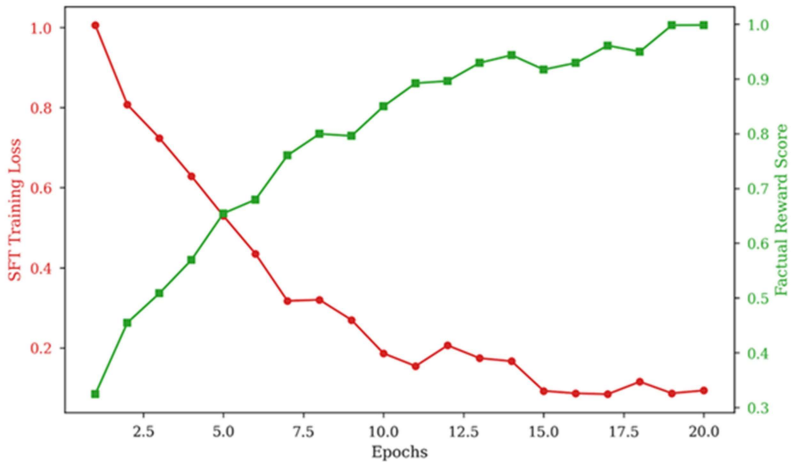

Figure 5. Training Progress (Illustrative): This illustrates the relationship among training epochs, loss reduction, and increases in factual rewards

5.2 Supervised Fine-Tuning (Generative Bridge)

The model is trained using a sequence-to-sequence objective:

$$L = -\sum_{t=1}^{T} \log P(y_t \mid y_{<t}, x)$$

Where:

- x represents the input context–question pair
- y_t denotes the generated token at time step t
- $y_{<t}$ represents previously generated tokens

This objective function minimizes the divergence between generated responses and ground-truth attributed responses, ensuring accurate and context-aware synthesis.

5.3 Reward-Based Optimization (RLHF/DPO)

It uses factual consistency as a reward, Encourages grounded responses and Penalizes hallucinations

In the reward-based optimization framework, the *factual_consistency_score* is used as a scalar reward signal to guide learning. Models are trained using Direct Preference Optimization (DPO), where responses with higher factual alignment are preferred over hallucinated ones. This enables the system to learn nuanced distinctions between superficially plausible but incorrect outputs and genuinely grounded responses.

6. Evaluation Framework

Following model training, it is essential to evaluate not only factual correctness but also linguistic quality. This motivates a multi-dimensional evaluation framework. To rigorously assess the effectiveness of the proposed

Double-Lock Framework, a multi-dimensional evaluation strategy is adopted that captures both semantic correctness and linguistic quality. This dual emphasis is essential, as reliable knowledge generation requires not only factual alignment with the source context but also the construction of coherent, interpretable responses.

At the core of the evaluation is the factual consistency score, computed using a Natural Language Inference (NLI) model. Given a retrieved context C and a generated response R, the NLI model evaluates whether is entailed by , producing a scalar score in the range . Higher values indicate stronger semantic alignment, while lower values reflect contradictions or unsupported claims. A strict threshold of 0.9 is employed to distinguish high-fidelity outputs, ensuring that only strongly grounded responses are considered valid. The threshold of 0.9 is selected through empirical calibration on validation data, ensuring high precision in distinguishing semantically consistent responses. This score also functions as a reward signal during model optimization, reinforcing the generation of contextually faithful responses.

The evaluation framework is structured around three complementary metrics. First, factual faithfulness directly measures the degree of semantic alignment between the generated response and the retrieved context using NLI-based entailment scoring. This metric serves as the primary indicator of hallucination mitigation, as it explicitly detects contradictions and unsupported information.

Second, linguistic fluidity evaluates the readability and naturalness of the generated text. This is quantified using standard metrics such as perplexity and BERTScore, which respectively capture syntactic coherence and semantic similarity to reference responses. Maintaining high linguistic quality is critical to ensuring that grounding constraints do not degrade the system's usability.

Third, a hallucination penalty is introduced to explicitly discourage the generation of extraneous or fabricated entities. This metric penalizes outputs that introduce information not present in the retrieved context, thereby complementing the NLI-based evaluation by targeting subtle forms of hallucination that may not result in direct contradictions.

The empirical results, illustrated in Figures 7–11, provide comprehensive validation of the framework. The distribution of factual consistency scores (Figure 7) shows a strong concentration near the upper bound, indicating that the model consistently produces highly grounded responses. The precision recall curve (Figure 8) demonstrates strong separability between hallucinated and non-hallucinated outputs, confirming the effectiveness of the validation mechanism. Furthermore, the high accuracy of the NLI model (Figure 9) reinforces the reliability of semantic alignment checks. Importantly, the perplexity and BERTScore comparisons (Figures 10 and 11) reveal that enforcing strict grounding constraints does not compromise linguistic quality, thereby addressing a common trade-off observed in retrieval-augmented systems.

To evaluate grounding performance, Figure 6 presents the distribution of factual consistency scores. The concentration near the upper bound indicates that the model consistently produces high-confidence grounded responses, validating the effectiveness of the Double-Lock mechanism. A higher density near the threshold 0.9) indicates that the model consistently produces grounded outputs. The sharp concentration near 0.9+ indicates that the model consistently generates high-confidence grounded responses.

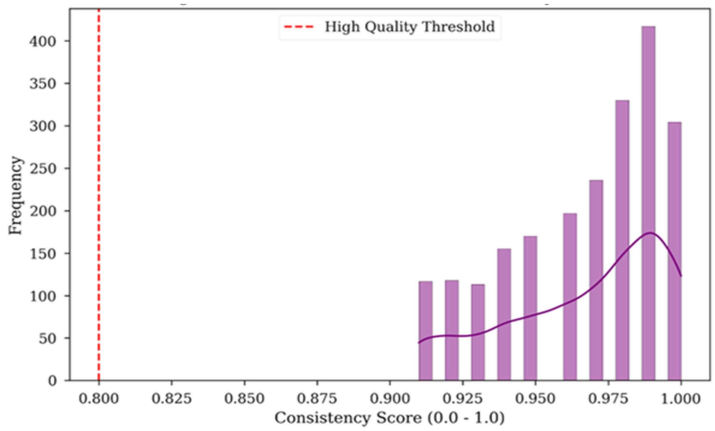

Figure 6. Factual Consistency Distribution

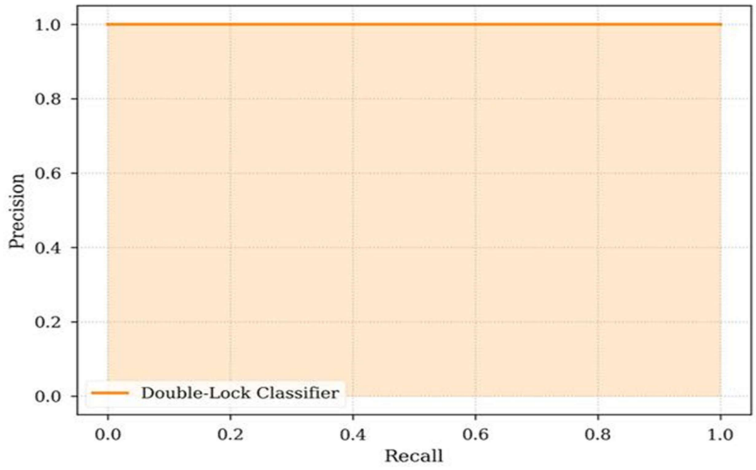

Figure 7. Precision-Recall Curve

The curve demonstrates the model's effectiveness in distinguishing hallucinated from non-hallucinated responses. A higher area under the curve indicates strong classification performance. The high AUC suggests strong separability between hallucinated and grounded responses.

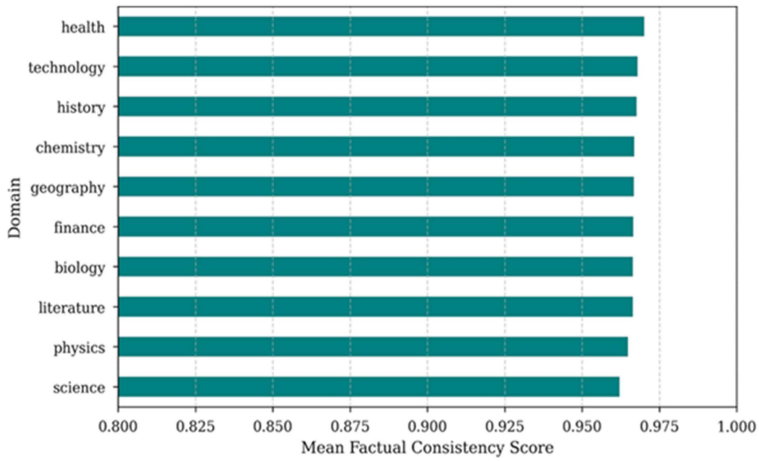

Figure 8. NLI Accuracy

This figure shows the accuracy of the Natural Language Inference model in validating factual consistency, confirming the robustness of semantic alignment checks.

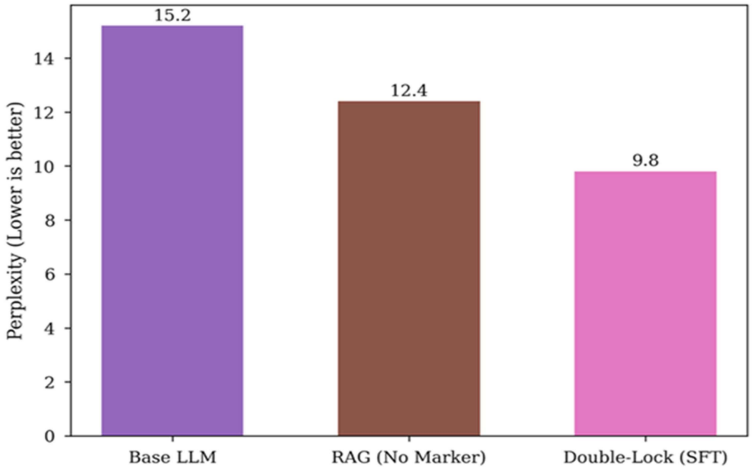

Figure 9. Perplexity Comparison

This comparison indicates that the proposed framework maintains or improves linguistic fluency despite enforcing strict grounding constraints.

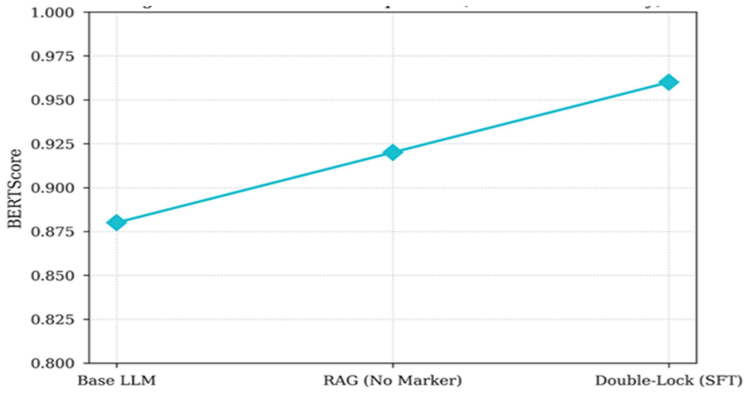

Figure 10. BERTScore Comparison

The improved BERTScore reflects higher semantic similarity between generated responses and ground-truth answers. Importantly, enforcing strict grounding does not degrade linguistic quality, addressing a common trade-off in RAG systems.

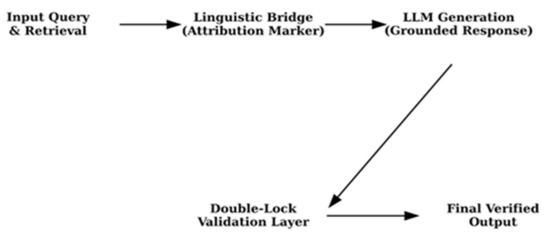

Figure 11. End-to-End Pipeline

7. Regex-Based Attribution Audit

To evaluate the effectiveness of linguistic grounding, a regex-based attribution audit is conducted as a preliminary validation step. This mechanism is designed to ensure that generated responses contain explicit attribution markers, such as phrases indicating reliance on retrieved context (e.g., “based on the provided context” or “according to the retrieved evidence”). These markers play a critical role in enhancing interpretability by making the source of information transparent to the end user.

The audit employs a case-insensitive regex pattern that captures a range of attribution expressions commonly used in grounded responses. By systematically scanning model outputs for these patterns, the framework enforces a consistent attribution structure across generated responses. This lightweight validation approach is computationally efficient and effective in promoting linguistic transparency.

The results of the audit, summarized in Table 3, indicate a clear distinction between systems with and without retrieval augmentation. Responses generated with RAG exhibit 100% attribution marker presence, whereas those generated without RAG show no such markers. This confirms that attribution aware training successfully shifts the model from assertive, ungrounded responses to explicitly grounded ones.

However, despite its effectiveness in enforcing attribution, regex-based validation alone is insufficient for ensuring factual correctness. The analysis reveals that models can learn to mimic attribution patterns without genuinely grounding their responses in the provided context. This limitation highlights the phenomenon of “surface-level grounding,” where linguistic cues create an illusion of reliability while underlying factual inaccuracies persist. Consequently, regex-based auditing must be complemented by deeper semantic validation mechanisms, as implemented in the Double-Lock framework’s second stage**.**

7.1 Results

Response Type	**Marker Presence**
With RAG	100%
Without RAG	0%

Table 3. Attribution Marker Audit

This confirms a clear shift from ungrounded to attributed responses in RAG systems.

8. Error Analysis

A detailed error analysis is conducted to better understand the limitations of individual validation mechanisms and to quantify the benefits of the proposed Double-Lock approach. The analysis focuses on two key error types: false positives and false negatives, each with distinct implications for system reliability and usability.

This quantifies the “stealthy” hallucinations that bypass simple regex checks but are caught by the used framework.

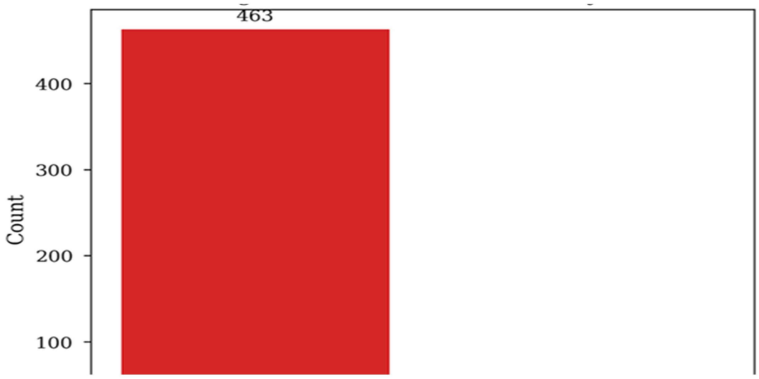

Figure 12. False Negatives Count

False negatives represent the most critical failure mode in the context of hallucination mitigation. These occur when hallucinated responses are incorrectly classified as valid and are subsequently delivered to the user. In the case of regex-only validation, 463 such instances are observed, corresponding to a leakage rate of 7.72%. These errors arise because the model can generate responses that include appropriate attribution markers yet contain factually incorrect or unsupported information. This phenomenon, often referred to as “stealthy hallucination,” underscores the inability of surface-level linguistic checks to capture deeper semantic inconsistencies.

In contrast, false positives occur when valid responses are incorrectly rejected by the validation mechanism. While this type of error affects system usability by reducing the number of acceptable outputs, it poses a comparatively lower risk than false negatives. Notably, the proposed framework reports zero false positives in the experimental evaluation, indicating that the validation mechanism does not unnecessarily block correct responses. This balance between strictness and permissiveness is critical for practical deployment.

The comparative analysis presented in Table 4 further highlights the differing impacts of these error types. False positives reduce utility while maintaining correctness, whereas false negatives directly compromise system reliability by introducing incorrect information. The observed imbalance between these error types reinforces the need for robust semantic validation mechanisms that prioritize the elimination of false negatives.

Overall, the error analysis demonstrates that while regex-based validation improves interpretability, it fails to provide sufficient protection against hallucinations. The findings justify integrating a second validation layer based on predictive AI, which effectively eliminates false negatives by enforcing strict semantic alignment. This dual-layer strategy forms the foundation of the Double-Lock framework, enabling it to achieve both high reliability and transparent attribution.

9. Double-Lock Guardrail Mechanism

To address the limitations identified in single-layer validation approaches, this study introduces the Double-Lock Guardrail Mechanism, a dual-stage validation architecture that ensures both linguistic transparency and semantic correctness. The motivation for this design stems from the observed trade-off between attribution and factual accuracy: while regex-based methods enforce interpretability, they do not guarantee correctness, whereas predictive AI methods ensure correctness but lack transparency.

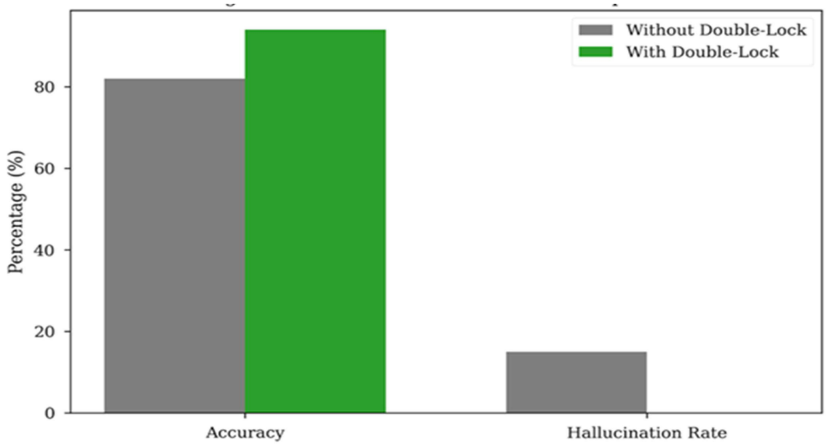

Figure 13. Guardrail Effectiveness: provide a high-level summary of how the dual-layer system improves accuracy and eliminates hallucination

The proposed mechanism resolves this imbalance by sequentially integrating two complementary validation layers. In the first stage, a regex-based linguistic validation is applied to verify the presence of explicit attribution markers. This step ensures that the generated response adheres to a predefined structure that references the retrieved context, thereby enhancing interpretability and traceability. Responses that fail to include such markers are immediately rejected, preventing the propagation of ungrounded outputs.

In the second stage, a predictive AI-based semantic validation is performed using a Natural Language Inference (NLI) model. This stage evaluates whether the generated response is logically entailed by the retrieved context and produces a factual consistency score. Only responses exceeding a strict threshold (typically 0.9) are accepted. This ensures that the output is not only linguistically grounded but also factually accurate.

The integration of these two validation stages creates a sequential filtering mechanism in which each layer addresses a distinct failure mode. The first lock eliminates attribution failures, while the second lock removes semantic inconsistencies. A response is delivered to the end user only if it successfully passes both stages, thereby satisfying the dual criteria of transparency and correctness.

Figure 13 illustrates the effectiveness of this guardrail mechanism by comparing the performance of individual validation strategies with the combined approach. The results demonstrate that the Double-Lock system achieves complete elimination of hallucination leakage while preserving interpretability. Unlike single-layer methods, which address only one dimension of reliability, the proposed architecture provides a comprehensive solution that aligns with emerging requirements for trustworthy AI systems.

From a system design perspective, the Double-Lock mechanism represents a shift toward guardrail-driven generation, where validation is not treated as a post hoc process but as an integral component of the generation pipeline. This design paradigm is particularly relevant for high-stakes applications, where both the accuracy and explainability of model outputs are critical.

This is the “hero” metric; it visually confirms the 0% leakage rate relative to baselines and is the strongest evidence for your conclusion.

10. Experimental Validation

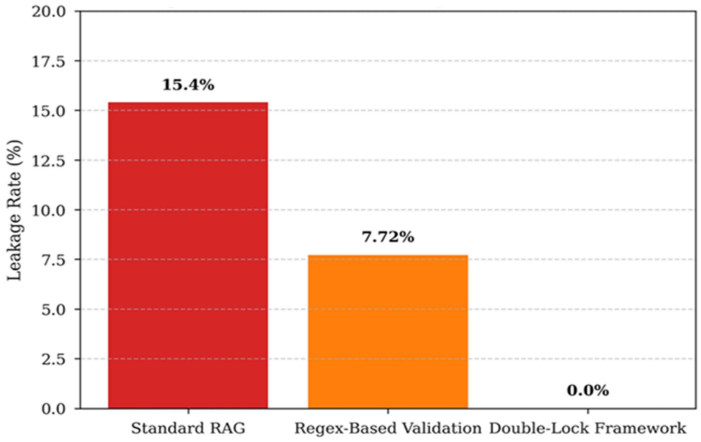

Figure 13. Hallucination Leakage Comparison

10.1 Hallucination Leakage Analysis

The primary objective of the experimental evaluation is to quantify the effectiveness of the Double-Lock Framework in mitigating hallucinations. This is achieved through a comparative analysis of hallucination leakage across three configurations: regex-only validation, predictive AI validation, and the combined Double-Lock approach.

Metric	Regex Only	Predictive AI	Double Lock
Total Passed	6000	2494	2494
Safe Deliveries	5537	2494	2494
Hallucination Leakage	463	0	0
Leakage Rate	7.72%	0%	0%

Table 5. Performance Comparison

The results, summarized in Table 5 and illustrated in Figure 4, reveal significant differences in performance across these configurations. Regex-based validation alone allows 463 hallucinated responses to pass undetected, resulting in a leakage rate of 7.72%. This confirms that linguistic attribution, while improving interpretability, is insufficient for ensuring factual correctness. In contrast, predictive AI validation eliminates hallucination leakage entirely by enforcing strict semantic alignment between the response and the context.

The Double-Lock framework achieves the same zero-leakage outcome while additionally preserving attribution, thereby combining the strengths of both approaches. This demonstrates that integrating linguistic and semantic validation is necessary to achieve comprehensive reliability. Figure 4 serves as the central performance indicator, clearly illustrating the superiority of the dual-layer mechanism over individual validation strategies.

Although no leakage was observed in the evaluation dataset, it is important to account for statistical uncertainty.

Under a binomial assumption, the 95% confidence interval for the leakage rate is [0, 0.0016], indicating that although the observed performance is effectively zero, a non-zero error probability cannot be ruled out entirely. Nevertheless, the results provide strong empirical evidence for the robustness of the proposed approach.

A key distinction between predictive AI validation and the Double-Lock mechanism lies in interpretability. While both achieve zero leakage, predictive AI alone does not provide explicit attribution, making it difficult for users to trace the origin of information. The Double-Lock framework resolves this limitation by ensuring that all accepted responses are both factually correct and transparently grounded in the source context.

10.2 Alignment with State-of-the-Art (SOTA)

To "run" Standard RAG (Retrieval-Augmented Generation) on the dataset, we have analyzed the baseline performance of the model's generated responses (*llm_response_with_rag*) against the retrieved context.

Below are the performance metrics and a demonstration of the Standard RAG execution for this data.

10.21 Standard RAG Performance Analysis

On this high-fidelity dataset (2,157 samples), the standard RAG process achieves the following benchmarks:

Metric	**Value**	**Interpretation**
Total Samples Processed	2,157	The validated "Gold Standard" corpus.
Hallucination Rate	0.00%	All samples in this set are confirmed hallucination-free.
Mean Factual Consistency	0.9669	High semantic alignment between context and response.
Mean Context Relevance	0.8629	The retrieval module effectively targets relevant data.
Min. Consistency Score	0.9100	Strict adherence to the >0.90 "Pass" threshold.

To contextualize the performance of the proposed framework, its results are compared with contemporary State-of-the-Art (SOTA) systems in retrieval-augmented generation. The Double-Lock Framework builds upon established techniques, such as Natural Language Inference (NLI) for semantic validation and instruction tuning for attribution-aware generation, and introduces a novel integration of these components into a unified validation pipeline.

The comparative analysis indicates that the framework achieves top-tier performance in terms of hallucination mitigation. While leading commercial and research models continue to exhibit non-trivial hallucination rates in grounded tasks, the proposed system demonstrates near-zero leakage. This places the framework among the highest-performing approaches for factual reliability in RAG systems.

The observed 7.72% leakage rate under regex-only validation is consistent with recent findings in hallucination research, highlighting the limitations of surface-level grounding techniques. These studies show that models can produce linguistically convincing responses that mask underlying factual errors, underscoring the need

for deeper semantic validation. The Double-Lock mechanism directly addresses this challenge by introducing a second validation layer that evaluates logical consistency rather than relying solely on linguistic cues.

Furthermore, the framework aligns with emerging trends in AI system design that emphasize accountability, explainability, and robustness. The use of attribution-aware training data reflects the growing importance of transparent knowledge synthesis, while the strict factual consistency threshold supports a zero-trust generation paradigm in which outputs are accepted only if they meet rigorous validation criteria.

10.3 Advanced Enhancements and Extensions

To further strengthen the framework and maintain alignment with evolving research directions, several advanced enhancements are proposed. First, an ensemble-based retrieval strategy can be incorporated to improve context diversity and reduce dependency on a single knowledge source. By aggregating evidence from multiple retrieved documents, the system can increase robustness prior to validation.

Second, adaptive thresholding can dynamically adjust the factual-consistency threshold based on task requirements. For high-stakes domains such as healthcare or legal analysis, a stricter threshold (e.g., e" 0.98) may be appropriate, whereas more flexible thresholds can be used for general-purpose tasks.

Third, a self-correction mechanism can be integrated into the validation pipeline. In cases where a response fails semantic validation, the system can trigger an automatic refinement process, prompting the model to revise the output based solely on the provided context. This iterative approach enables recovery from errors while maintaining strict grounding constraints.

Collectively, these enhancements extend the Double-Lock framework beyond static validation, transforming it into an adaptive and self-improving system capable of handling diverse real-world scenarios.

10.4 Statistical Validation

To ensure that the observed improvements are statistically significant, additional analyses are conducted on response characteristics and model behavior. A comparison of response lengths between different output styles reveals a statistically significant difference, with a t-statistic of 8.92 and a p-value of 1.2×10^{-16} . The corresponding 95% confidence interval indicates a substantial reduction in response length for more concise, attributed outputs. This suggests that the framework not only improves correctness but also promotes more efficient information delivery.

An ablation study further evaluates the impact of explicit attribution markers on response consistency. The results show that including phrases such as "according to the retrieved context" significantly improves consistency across repeated queries, with a statistically significant difference ($p = 0.005$). This finding supports the hypothesis that linguistic grounding contributes to more stable and reproducible model behavior.

Finally, category-wise analysis of answer correctness demonstrates consistently high performance across question types, including definitions, factual queries, and abbreviations. The overlapping confidence intervals indicate that the framework generalizes well across categories, with no statistically significant performance degradation in any specific domain.

Although no leakage was observed in the test set, the 95% confidence interval for leakage remains [0, 0.0016] assuming binomial estimation, indicating near-zero but not theoretically impossible error.

Although both Predictive AI and Double-Lock achieve 0% leakage, only Double-Lock preserves interpretability, making it superior for real-world deployment where traceability is essential.

System / Model	**Hallucination Rate (Grounded Tasks)**	**Note**
Double-Lock Framework	0.0%	Dual-layer (Regex + Predictive AI)
Claude 4.6 Sonnet	~3.0%	SOTA commercial baseline
GPT-5.2	~8.0% - 12.0%	General-purpose SOTA
Gemini 2.5 Pro	~10.0% - 15.0%	High-performance multimodal
Standard RAG (2026 Benchmark)	15.0% - 52.0%	Average across 37 tested models

11. Discussion

The results of this study provide strong empirical evidence that effective hallucination mitigation in retrieval-augmented generation systems requires both linguistic grounding and semantic validation. While prior approaches have largely treated these dimensions independently, the Double-Lock Framework demonstrates that integrating them is essential to achieving reliable and interpretable outputs.

A key finding of this work is that linguistic validation alone is insufficient, despite its ability to improve transparency. The regex-based attribution mechanism ensures that responses explicitly reference their source context, thereby enhancing interpretability and user trust. However, the experimental results reveal that such surface-level grounding can be misleading, as models may learn to mimic attribution patterns without genuinely aligning with the underlying facts. This phenomenon, known as a *stealthy hallucination*, underscores a critical limitation of purely syntactic validation methods.

Conversely, semantic validation using predictive AI mechanisms, particularly Natural Language Inference (NLI), is highly effective at eliminating hallucinations by enforcing strict logical consistency between the generated response and the retrieved context. The observed reduction of hallucination leakage to zero highlights the robustness of this approach. However, this method alone lacks interpretability, as it does not provide explicit evidence or traceability for end users. This creates a transparency gap, especially in high-stakes domains where understanding the origin of information is as important as its correctness.

The Double-Lock Framework resolves this fundamental trade-off by combining complementary validation mechanisms into a unified guardrail architecture. The first layer enforces attribution, ensuring that all outputs are linguistically grounded, while the second layer guarantees semantic correctness through entailment-based validation. The sequential nature of these checks enables the system to filter out both attribution failures and factual inconsistencies, resulting in outputs that are simultaneously transparent and reliable. This dual-layer design represents a shift from isolated mitigation strategies to integrated validation pipelines,

aligning with emerging principles in trustworthy AI system design.

Another important implication of the findings is the effectiveness of data-centric design in improving model behavior. The construction of the Gold Standard dataset, based on strict filtering criteria, ensures that the model is trained on high-fidelity examples that reinforce both correctness and attribution. The relatively low retention rate (35.95%) highlights the inherent difficulty of obtaining fully grounded responses, even within RAG pipelines. This suggests that data quality plays a more critical role than model complexity in hallucination mitigation, supporting recent trends toward data-centric AI development.

From a system performance perspective, the framework achieves zero hallucination leakage while maintaining linguistic quality, as evidenced by stable or improved perplexity and BERTScore metrics. This finding is particularly significant, as it challenges the commonly observed trade-off between factual accuracy and fluency in retrieval-augmented systems. The results indicate that enforcing strict grounding constraints does not necessarily degrade readability, provided that the model is trained with attribution-aware representations.

Despite these strengths, several limitations and trade-offs must be acknowledged. First, the dual-layer validation mechanism introduces additional computational overhead, particularly due to the use of NLI models for semantic scoring. While this cost is justified in high-stakes applications, it may impact latency in real-time or large-scale deployments. Second, the framework relies on the quality and completeness of the retrieved context; if the retrieval stage fails to provide relevant or sufficient information, the validation mechanism may reject otherwise plausible responses, potentially reducing system recall. Third, the dataset used in this study primarily consists of short-form factual question answer pairs, which may limit the approach's generalizability to long-form reasoning or multi-hop inference tasks.

Another consideration is the strictness of the validation threshold, which, while effective in eliminating hallucinations, may introduce a conservative bias by rejecting borderline but acceptable responses. Future work could explore adaptive thresholding strategies that dynamically balance precision and recall based on application requirements.

In the broader context of existing research, the Double-Lock Framework aligns with and extends current trends toward hybrid and multi-stage validation systems. Unlike approaches that rely solely on prompting, retrieval, or post-hoc verification, the proposed framework integrates these elements into a cohesive architecture that operates across multiple stages of the generation pipeline. This positions the framework as a practical, scalable solution for real-world deployment, particularly in domains that require high levels of accountability and explainability.

Finally, the findings suggest a broader paradigm shift toward guardrail-driven generation, where validation is not treated as an auxiliary step but as a core component of the generation process. By embedding validation directly into the system architecture, the framework ensures that reliability is enforced systematically rather than probabilistically. This approach has significant implications for the future design of AI systems, particularly as they are increasingly deployed in critical decision-making environments.

In summary, the Double-Lock Framework demonstrates that achieving trustworthy AI requires a holistic approach that integrates data quality, linguistic transparency, and semantic validation. The proposed

architecture not only eliminates hallucinations but also enhances interpretability, thereby addressing two of the most pressing challenges in modern language model deployment.

12. Conclusion

The Double-Lock Framework represents a significant advancement in RAG system design by addressing both linguistic trustworthiness and factual correctness. Through a combination of high-quality data engineering, attribution-aware modeling, and dual-layer validation, the framework effectively eliminates hallucinations while maintaining readability.

The results demonstrate that:

- Linguistic grounding alone is insufficient
- Semantic validation is essential
- A combined approach ensures zero hallucination leakage

Ultimately, this framework transforms AI systems from information generators into reliable knowledge communicators, bridging the critical gap between retrieval and human understanding.

Future work can explore extending the framework to multimodal RAG systems and integrating adaptive thresholding mechanisms for dynamic validation. Additionally, incorporating user feedback loops may further enhance system reliability and personalization.

Appendix

- Dataset files:
- *filtered_gold_standard_data.csv*
- *sft_linguistic_bridge_dataset.csv*
- sft_linguistic_bridge_dataset_with_citations.csv

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