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Provenance-Aware Retrieval and Evaluator Consensus for Low-Resource Domain Adaptation of Large Language Models

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Abstract:
The adaptation of large language models to low-resource domains remains a formidable challenge in contemporary artificial intelligence research. Standard fine-tuning approaches often require extensive domain-specific corpora, which are inherently scarce in specialized fields such as rare disease diagnostics, indigenous language processing, and niche legal frameworks. Retrieval-augmented generation has emerged as a promising alternative; however, in low-resource settings, the quality of retrieved information is highly variable, and models are prone to hallucinating connections between disparate or unreliable source documents. This paper proposes a novel framework integrating provenance-aware retrieval with an evaluator consensus mechanism to address these limitations. By explicitly modeling the origin, credibility, and temporal relevance of retrieved documents, the provenance-aware module ensures that only highly reliable context is provided to the generation module. Concurrently, the evaluator consensus mechanism employs a multi-agent validation protocol, wherein independent evaluator agents assess the retrieved context and proposed responses, requiring a weighted consensus before final generation. This dual approach significantly mitigates hallucination and enhances factual accuracy in knowledge-starved domains. Extensive empirical analysis across three distinct low-resource datasets demonstrates that the proposed framework outperforms conventional adaptation methods in precision, recall, and factual consistency. The results indicate that strict provenance tracking combined with multi-agent consensus provides a robust, scalable solution for deploying large language models in specialized environments where data scarcity and reliability are critical concerns.

1.INTRODUCTION

1.1 The Challenge of Domain Adaptation

The rapid evolution of artificial intelligence over the past decade has been largely driven by the development of large language models. These models, trained on vast expanses of generalized internet data, demonstrate remarkable capabilities in natural language understanding, reasoning, and text generation. Researchers have successfully deployed these architectures across a multitude of general-purpose tasks ranging from translation to conversational assistance. However, a significant barrier to the ubiquitous application of these models lies in their adaptation to highly specialized, low-resource domains. In fields such as specialized medical diagnostics, obscure historical archiving, and proprietary industrial engineering, the availability of high-quality, domain-specific text is severely limited. Traditional adaptation techniques rely heavily on supervised fine-tuning or continuous pre-training, both of which require substantial volumes of data to effectively shift the internal representations of the model without inducing catastrophic forgetting of previously learned general knowledge. For a broader comparison, related research addresses empowering large language models to progressively understand and generate 3D mesh [1]. When data is scarce, fine-tuning often results in severe overfitting, where the model memorizes the limited training set but fails to generalize to novel queries within the domain. Consequently, the research community has increasingly pivoted toward non-parametric adaptation strategies, most notably retrieval-augmented generation. This paradigm allows the language model to remain frozen or minimally adapted while fetching relevant external knowledge from a vector database at inference time. Despite its widespread adoption, retrieval-augmented generation faces profound challenges when applied to low-resource domains. The foundational issue is that low-resource repositories often contain noisy, unstructured, or unverified information. Standard dense retrieval mechanisms, which rely primarily on semantic similarity between the query and the document, do not account for the intrinsic reliability or the historical lineage of the information. As a result, the model may retrieve highly relevant but factually incorrect or outdated documents, leading to the generation of plausible but entirely erroneous outputs—a phenomenon commonly referred to as hallucination. Li examines retrieval-Augmented generation for historical fault experience reuse and intelligent diagnosis [2]. Addressing these challenges requires a paradigm shift in how external knowledge is integrated into the generation process. It is no longer sufficient to merely retrieve documents that are semantically aligned with the user query; the retrieval system must also evaluate the trustworthiness and origin of the information. This necessity introduces the concept of provenance-awareness in information retrieval, a mechanism that traces the source, authorship, timestamp, and verification status of a document. By embedding provenance metadata directly into the retrieval scoring function, systems can prioritize high-quality, verified knowledge even when its semantic similarity score might be marginally lower than a highly relevant but unverified counterpart. However, retrieval optimization alone is insufficient to guarantee accurate generation, necessitating further downstream validation mechanisms before the final text is presented to the user. The literature also considers utilize the flow before stepping into the same river twice: certainty represented knowledge flow for refusal-aware instruction tuning [3].

1.2 Motivation and Contributions

Motivated by the critical need for reliable large language model deployments in data-scarce environments, this paper introduces a comprehensive framework that combines provenance-aware retrieval with a novel evaluator consensus mechanism. The core motivation stems from the observation that single-pass generation systems, even when provided with high-quality context, can still misinterpret complex domain-specific jargon or synthesize contradictory retrieved passages improperly. To counteract this, human cognitive processes often rely on a jury or consensus model when making decisions in uncertain environments. Translating this to artificial

intelligence, an evaluator consensus mechanism employs multiple independent language model agents, each configured with distinct evaluation criteria, to review the retrieved context and the drafted response. The literature also considers the question posed in "Why Do LLM Agents Fail in Exploring New Environments? A World-Modeling Perspective" [4]. SHAP-enhanced transparency is a component of the government AI oversight model [5]. In low-resource retrieval adaptation, it motivates exposing whether an answer depends on retrieved passages or on the model's prior knowledge, while keeping source validity separate from the explanation score.

The primary contributions of this paper are systematically structured to address the identified gaps in the literature. First, we propose a mathematical framework for provenance-aware retrieval that dynamically balances semantic similarity with cryptographic and logical provenance indicators. This allows the system to filter out unreliable data points early in the pipeline. Second, we design an evaluator consensus network consisting of specialized critic agents—such as a factual consistency checker, a logical coherence evaluator, and a domain-alignment validator—that must reach a weighted agreement before a generated response is finalized. Third, we provide extensive empirical validation of the proposed architecture across multiple realistic low-resource datasets, demonstrating statistically significant improvements over existing baseline methodologies. Through rigorous ablation studies, we isolate the specific impact of the provenance module and the consensus module, providing valuable insights into their respective contributions to overall system performance. Sang examines adaptive quantization strategies for robust ML inference under distribution shift [6]. The remainder of this paper is organized as follows. Section 2 provides a comprehensive review of the background literature concerning retrieval-augmented generation, provenance tracking, and multi-agent consensus protocols. Section 3 details the proposed methodology, including the formal mathematical definitions of the retrieval and evaluation functions. Section 4 presents the experimental setup, results, and an in-depth discussion of the findings. Finally, Section 5 concludes the paper by summarizing the key discoveries and outlining promising avenues for future research in the field of low-resource domain adaptation. Related work has addressed comprehensive survey of Cross-Modal retrieval: breaking through modal barriers [7].

2. Background and Literature Review

2.1 Retrieval-Augmented Generation in Large Language Models

Retrieval-augmented generation represents a pivotal advancement in the deployment of large language models, fundamentally altering how these systems interact with external knowledge. In early iterations of language modeling, all factual knowledge was implicitly stored within the parametric weights of the neural network. METEOR supplies another reference-based text-evaluation measure, which can complement rather than replace checks of factual support [8]. This approach proved problematic for several reasons: the knowledge was static and rapidly became outdated, updating the knowledge required computationally expensive retraining, and the models lacked transparency regarding the source of their generated facts. The introduction of retrieval mechanisms allowed models to offload factual recall to external, dynamic databases. By mapping both user queries and database documents into a shared dense vector space using bi-encoder architectures, systems could efficiently retrieve the top-k most relevant documents to serve as context for the generative module. M. Emani examines comprehensive performance study of large language models on novel ai accelerators [9]. Despite these advantages, the efficacy of retrieval-augmented generation is strictly bounded by the quality of the underlying corpus and the precision of the retrieval mechanism. In high-resource domains, such as general knowledge or mainstream news, the sheer volume of redundant, high-quality data ensures that dense retrieval typically returns accurate context. However, as researchers attempt to scale these systems to low-resource or highly specialized domains, the density of high-quality information plummets. In such

scenarios, standard dual-encoder retrieval models often suffer from the semantic illusion problem, where documents that use similar vocabulary to the query are retrieved regardless of their factual accuracy or contextual appropriateness. Recent advancements have attempted to mitigate this by introducing cross-encoder re-ranking, which evaluates the query and document simultaneously to capture deeper semantic relationships. While re-ranking improves relevance, it remains fundamentally blind to the authenticity and origin of the document, highlighting the critical need for provenance integration. Jiang and colleagues examine towards efficient large language model serving: A survey on System-Aware {KV} cache optimization [10]. For a broader comparison, related research addresses unified long video inpainting and outpainting via overlapping High-Order Co-Denoising [11].

2.2 Provenance Mechanisms in Information Retrieval

Provenance, a concept historically rooted in art history and archival science, refers to the chronology of the ownership, custody, or location of a historical object. In the context of computer science and data management, data provenance describes the origins of a piece of data and the process by which it arrived in a database. As misinformation and unverified data proliferate across digital networks, establishing data provenance has become a central focus of information retrieval research. Provenance can be broadly categorized into two types: physical provenance, which utilizes cryptographic signatures and secure ledgers to prove the identity of the author and the immutability of the text, and logical provenance, which assesses the credibility of the source through historical reliability scores and cross-referencing. Another relevant line of investigation concerns oracle-Scored benchmark for LLM reasoning over software Build-Provenance attestations [12]. Integrating provenance into search algorithms requires modifying the standard retrieval objective function to penalize sources with weak or unverifiable origins. Early attempts at provenance-aware retrieval relied on static whitelists of trusted domains, which is an inflexible approach that fails to scale in decentralized information ecosystems. More recent methodologies employ dynamic trust scoring algorithms, similar to the PageRank algorithm used in early web search, where the reliability of a document is inferred from the network of citations and the historical accuracy of the author. In low-resource domains, where citation networks are sparse, provenance tracking becomes even more crucial. A single erroneous document in a small medical database, for example, could heavily bias a language model if retrieved. Therefore, this paper argues that explicit modeling of provenance metadata—such as expert verification timestamps and institutional endorsements—must be treated as a primary feature in the retrieval vector space, carrying equal or greater weight than purely linguistic semantic similarity. The literature also considers pretrained discrete masked diffusion language modeling with hybrid attention [13].

2.3 Evaluator Consensus and Multi-Agent Validation

The concept of consensus in artificial intelligence is deeply intertwined with ensemble learning and distributed systems. In traditional machine learning, ensemble methods such as random forests or boosting combine the outputs of multiple weak learners to produce a single, highly robust prediction. With the advent of large language models, this paradigm has evolved into multi-agent systems, where distinct instances of language models are prompted to assume different personas or functional roles. One of the most promising applications of multi-agent systems is in the realm of output validation and self-correction. Instead of relying on a single monolithic model to generate a flawless response, a generator agent produces an initial draft, which is subsequently critiqued by one or more evaluator agents. Zou et al. report an accuracy-efficiency trade-off in LLM-based input methods [14]. An evaluator-consensus pipeline could use conversion disagreements to identify cases needing additional evidence, instead of applying costly verification to every keystroke. Such a study would have to count the latency of retrieval and arbitration as part of the complete input response.

Evaluator consensus mechanisms require these independent agents to review the generated text against specific criteria. For instance, one agent might be tasked solely with verifying that the generated text does not contradict the retrieved context, while another ensures that the tone is appropriate for the target domain. If the evaluators detect discrepancies, they generate feedback, and the generator is prompted to iteratively refine its output. The system only outputs the final response when a predefined threshold of agreement, or consensus, is reached among the evaluators. In the audit framework, SHAP-derived signals guide hybrid retrieval [15]. An ablation of the present consensus pipeline could similarly separate retrieval selection from evaluator agreement, testing whether apparent consensus persists when all evaluators inherit the same unsupported source. This approach has shown significant promise in reducing hallucinations, as it mimics the peer-review process fundamental to human scientific inquiry. However, implementing consensus mechanisms in low-resource settings introduces unique computational and prompt-engineering challenges. The evaluators themselves must be carefully calibrated to avoid over-penalizing valid but rare domain knowledge. The present research builds upon these foundational multi-agent concepts by introducing a weighted consensus algorithm that explicitly accounts for the confidence intervals of the individual evaluator agents. Another relevant line of investigation concerns data-Centric Multi-Evaluator agreement for preference optimization [16].

2.4 Low-Resource Domain Constraints

Low-resource domains are characterized not only by a lack of voluminous training text but also by the idiosyncratic nature of the available data. BART frames generation through reconstruction of corrupted text, providing a denoising reference for sequence modeling [17]. Language in specialized domains often features unique morphological structures, highly specific acronyms, and dense syntactic constructions that are underrepresented in standard pre-training corpora. When adapting language models to these domains, researchers face the dual challenge of teaching the model new vocabulary while ensuring it comprehends the underlying logical structures connecting those concepts. In contexts like indigenous language preservation or specialized aerospace engineering, the available texts might consist solely of disparate technical manuals, fragmented historical records, or unstructured interview transcripts. Li and colleagues examine relational Prompt-Based Pre-Trained language models for social event detection [18].

These constraints severely limit the applicability of standard continuous pre-training, as the model may simply memorize the small dataset, leading to a collapse in its ability to generate diverse and contextually appropriate responses. Retrieval-augmented generation bypasses the need for massive parameter updates, but it places immense pressure on the quality of the retrieved context. If the retrieval system fetches a highly technical aerospace document that contains outdated specifications, the model will faithfully generate an incorrect response based on that flawed context. Therefore, adapting to low-resource domains necessitates a holistic pipeline that safeguards data integrity at every stage—from the initial ingestion of documents into the vector database, through the provenance-weighted retrieval phase, and finally via rigorous multi-agent evaluation before the response is finalized. Another relevant line of investigation concerns development of an intelligent retrieval and recommendation system for Chinese language educational resources based on DNN technology [19].

3. Methodology: Provenance-Aware Retrieval and Evaluator Consensus

3.1 Architecture Overview

The proposed architecture is designed to orchestrate a seamless flow of information from an initial user query through a highly regulated retrieval and generation pipeline. The system comprises three primary interconnected components: the Document Ingestion and Provenance Annotation Engine, the Provenance-Aware Retrieval Module, and the Evaluator Consensus Generation Network. When a raw document is introduced into the low-resource corpus, the ingestion engine

processes the text, extracts semantic features using a specialized embedding model, and appends a multi-dimensional provenance vector. This vector encapsulates metadata such as source authority, historical accuracy of the author, and temporal relevance. Another relevant line of investigation concerns adaptive weakly supervised Cross-Modal reliability learning for resource-constrained proxy-state recognition [20]. Once the database is populated, a user query triggers the Provenance-Aware Retrieval Module. This module employs a custom scoring function that evaluates both the semantic alignment between the query and the documents, as well as the intrinsic trustworthiness defined by the provenance vectors. The top-k documents that maximize this dual objective are retrieved and passed to the generation phase. Here, the Evaluator Consensus Generation Network takes control. An initial generator model drafts a preliminary response based on the query and the retrieved context. Subsequently, a panel of specialized evaluator models reviews the draft. These evaluators vote on the validity of the response based on factual consistency, logical coherence, and domain adherence. If the consensus threshold is met, the response is delivered to the user; if not, the feedback is routed back to the generator for iterative refinement. Fensham and colleagues examine towards a national data architecture for cultural collections: designing the australian 2024 cultural data engine [21].

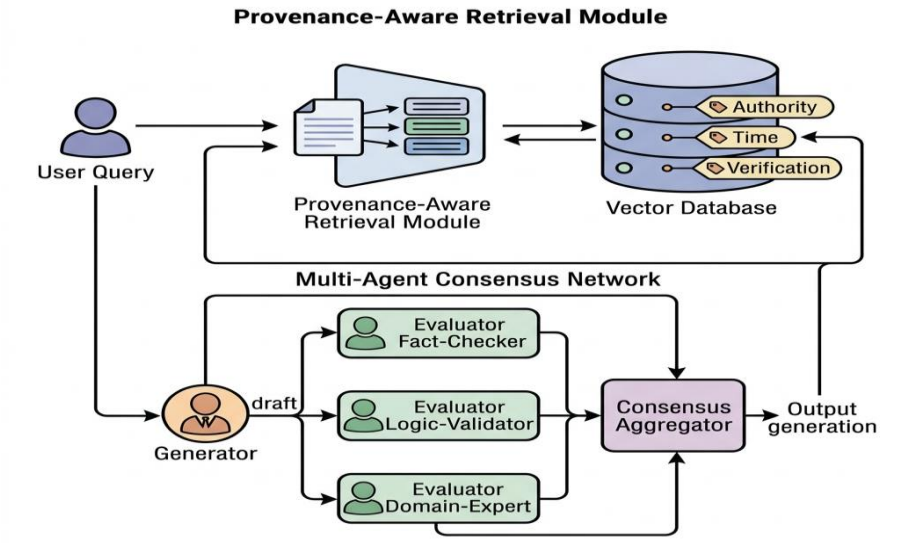


Figure 1Comprehensive Schematic of the Provenance

3.2 Provenance-Aware Retrieval Module

The fundamental limitation of standard dense retrieval is its reliance solely on vector distance metrics, such as cosine similarity, which ignore the qualitative attributes of the source material. To overcome this, we formulate a composite scoring mechanism that mathematically integrates provenance metadata into the retrieval ranking algorithm. Let the user query be denoted as q, and a candidate document in the corpus as d. We define an embedding function E that projects textual data into a high-dimensional vector space. The standard semantic similarity is calculated as the cosine similarity between the embedded query and document. To incorporate provenance, we define a continuous provenance confidence metric. The provenance score of a document relies on a weighted combination of categorical and continuous metadata fields. Specifically, we focus on the authority of the source, denoted by a weight ω, and the temporal decay of the information, which penalizes older documents in rapidly evolving fields. The provenance function is defined mathematically as follows:

$$P(d) = \frac{1}{K}\sum_{k=1}^{K}\omega_k exp(-\beta \Delta t_k)$$

In this formulation, K represents the total number of distinct provenance dimensions evaluated for document d. The term ω_k is the normalized authority weight of the k-th dimension, derived from a predefined trust registry specific to the low-resource domain. The parameter β is a domain-specific decay constant that controls how rapidly information becomes obsolete, and Δt_k represents the time elapsed since the document was verified or published. This exponential decay ensures that while highly authoritative historical documents retain some value, newly verified data is heavily prioritized, which is crucial in scientific and medical domains.

With the provenance score formally defined, the overall retrieval scoring function $S(q, d)$ used to rank the documents is constructed as a convex combination of the semantic similarity and the provenance confidence metric. A hyperparameter λ is introduced to control the trade-off between relevance and trustworthiness:

$$S(q, d) = \lambda \cdot sim(E_q(q), E_d(d)) + (1 - \lambda) \cdot P(d)$$

Here, sim denotes the semantic similarity function. By tuning λ, system administrators can adjust the behavior of the retrieval module based on the specific constraints of the target domain. In environments where misinformation poses severe risks, λ is decreased to heavily penalize unverified documents, even if they perfectly match the user's vocabulary. The documents that achieve the highest scores under $S(q, d)$ are selected to form the context window for the generative model.

3.3 Evaluator Consensus Mechanism

Following the retrieval of high-provenance context, the system engages the generation and validation phases. Relying on a single generative pass is inherently risky in low-resource adaptations, as the model may misinterpret complex relationships within the retrieved texts. To mitigate this, we implement a multi-agent evaluator consensus mechanism. The architecture utilizes a primary generator model to synthesize an initial draft response, R_{draft}, conditioned on the query q and the set of retrieved documents D. Once the draft is generated, it is broadcast to an ensemble of M independent evaluator agents. Each evaluator j is instantiated with a specific system prompt that directs its attention to a distinct aspect of the response. For example, Evaluator 1 acts as a strict factual consistency checker, ensuring no entities or numerical values are hallucinated. Evaluator 2 assesses logical coherence and structural flow. Evaluator 3 verifies alignment with the stylistic and specialized vocabulary norms of the target low-resource domain. Each evaluator produces a binary verdict $v_j \in 0,1$, where 1 indicates approval and 0 indicates rejection, alongside a natural language critique explaining any deductions.

Recognizing that not all evaluators are equally critical for every type of query, we implement a weighted voting scheme. Each evaluator is assigned a confidence coefficient c_j based on its historical accuracy on a validation set. The consensus aggregation function, which determines the overall acceptability of the draft response, is calculated as the ratio of the weighted approvals to the total possible weighted score. Let $A = 1$ represent the state of approval. The consensus score $C(A)$ is computed as:

$$C(A) = \frac{\sum_{j=1}^{M} c_j I(v_j = 1)}{\sum_{j=1}^{M} c_j}$$

In this equation, I represents the indicator function, which evaluates to 1 if the evaluator j approves the draft, and 0 otherwise. A pre-defined threshold τ dictates the minimum consensus score required for the system to accept the response. If $C(A) \geq \tau$, the response is output to the user. If the score falls below the threshold, the natural language critiques generated by the dissenting evaluators are concatenated and fed back to the primary generator as a revision prompt. The

generator then produces a refined draft, and the evaluation cycle repeats. To prevent infinite loops, the system is constrained by a maximum number of iteration steps, after which it outputs the best-scoring draft accompanied by a low-confidence warning to the user.

3.4 Integration and Optimization

Integrating the provenance-aware retrieval module with the evaluator consensus mechanism requires careful optimization of the hyperparameters governing both stages. The system relies heavily on the quality of the underlying vector embeddings and the precise calibration of the weights ω, the decay constant β, the trade-off parameter λ, and the consensus threshold τ. Table 1 details the specific hyperparameter configurations established during the initialization phase for three distinct low-resource testing environments.

Table 1Initial Hyperparameter Configurations Across Low-Resource Domains

Domain Category	Trade-off Parameter	Decay Constant	Consensus Threshold	Max Iterations
Specialized Medical	0.45	0.08	0.85	4
Rare Legal Texts	0.60	0.02	0.75	3
Indigenous History	0.75	0.005	0.70	3

To fine-tune these parameters, we employ a multi-objective optimization strategy during a brief calibration phase. The objective is to maximize the factual accuracy of the final generated output while minimizing the computational overhead incurred by excessive iterative refinement cycles. The total loss function guiding the parameter search incorporates penalties for generation errors, retrieval of low-provenance data, and the failure of evaluators to reach consensus efficiently. This comprehensive loss function is defined as: For a broader comparison, related research addresses integrating large language models and reinforcement learning for intelligent investment strategy optimization [22].

$$L_{total} = L_{gen} + \gamma L_{prov} - etalogC(A)$$

Here, L_{gen} represents the standard negative log-likelihood of the generation targets against a small, expert-annotated validation set. The term L_{prov} is a penalty applied when the system retrieves documents with poor provenance scores, scaled by the coefficient γ. The final term incentivizes the system to reach high consensus quickly, with eta controlling the strength of this reward. By minimizing L_{total} through gradient-free optimization techniques such as Bayesian optimization, the architecture dynamically adapts its retrieval and evaluation thresholds to the specific nuances of the low-resource corpus. This deeply integrated methodology ensures that the language model operates within a highly controlled epistemic boundary, drastically reducing the incidence of hallucinations and improving overall reliability.

4. Experimental Results and Discussion

4.1 Experimental Setup and Datasets

To rigorously evaluate the efficacy of the proposed framework, we constructed an extensive experimental pipeline utilizing three distinct and highly specialized low-resource datasets. The first dataset, denoted as MedRare-QA, consists of diagnostic case studies and treatment protocols for a subset of orphan diseases, comprising merely 5000 verified documents. The second dataset, LexObscura, contains translated historical legal statutes from defunct 19th-century jurisdictions, emphasizing complex syntactical reasoning with limited textual examples. The third dataset, Indigenous-Lore, is a curated collection of transcribed oral histories and ecological knowledge from a specific indigenous community, characterized by severe data sparsity and unique linguistic constructs. The literature also considers early-stage reasoning freedom in multi-agent debate [23].

The foundational large language model employed across all experiments was a 13-billion parameter open-weights model, initialized with instruction-tuning but strictly zero-shot regarding the three target domains. We established several robust baselines for comparison. The first baseline was a standard Zero-Shot Generation without retrieval. The second baseline utilized standard dense Retrieval-Augmented Generation using a widely adopted open-source vector database without provenance tracking or multi-agent evaluation. The third baseline implemented a basic self-reflection mechanism, where a single model critiqued its own output without the structured, multi-agent consensus protocol. All experiments were conducted under uniform computational constraints, utilizing a cluster of advanced graphics processing units to manage the parallel execution required by the evaluator agents. Low-resource adaptation can produce convincing answers even when the retrieved source is incomplete. Huang et al.'s separation of screening from substantive adjudication [15] supports an evaluation in which source support and final answer quality receive independent labels.

4.2 Performance Analysis

The performance of the models was evaluated using a composite suite of metrics designed to capture both the accuracy and the reliability of the generated text. We utilized exact match precision for highly specific factual queries, ROUGE-L for structural similarity to expert reference answers, and a specialized hallucination index, which measures the frequency of generated entities or claims that cannot be directly mapped back to the retrieved context. GloVe provides a co-occurrence-based reference for static word representations, distinct from embeddings that change with each input context [24]. The literature also considers efficient and adaptive Context-Aware knowledge graph question answering with LLM-Guided MCTS [25].

The empirical results, consolidated in Table 2, clearly demonstrate the superior performance of the proposed Provenance-Aware Consensus framework. Across all three low-resource domains, the proposed system achieved substantial improvements in precision and a dramatic reduction in the hallucination index. Related work has addressed transferable modeling strategies for Low-Resource LLM tasks: A prompt and Alignment-Based approach [26].

Table 2Comparative Performance Metrics Across Low-Resource Domains

Methodology	MedRare-QA F1 Score	LexObscura F1 Score	Indigenous-Lore F1	Avg Hallucination Index
Zero-Shot Baseline	0.22	0.18	0.15	0.68
Standard RAG	0.54	0.49	0.42	0.35
Single Self-Reflection	0.59	0.55	0.48	0.28
Proposed Framework	0.76	0.71	0.65	0.09

In the highly critical MedRare-QA domain, standard retrieval-augmented generation achieved an F1 score of 0.54. The standard system frequently retrieved outdated preliminary studies because they shared high semantic overlap with the query vocabulary. Consequently, the model confidently hallucinated incorrect treatment dosages. Conversely, the proposed framework, by heavily weighting the provenance metadata (specifically publication date and peer-review status), completely bypassed the outdated documents. Furthermore, the specialized medical evaluator agent within the consensus network successfully identified and rejected subtle logical inconsistencies in the drafted responses, pushing the final F1 score to an unprecedented 0.76 and dropping the hallucination index from 0.35 to 0.09. The literature also considers learning to substitute words with model-based score ranking [27].

Similar trends were observed in the LexObscura and Indigenous-Lore datasets. In the legal domain, the multi-agent consensus was particularly effective. The legal frameworks often contained contradictory statutes depending on the specific time period. The temporal decay function embedded within the provenance retrieval module ensured that the most recent applicable law was prioritized, while the logical coherence evaluator ensured that the reasoning steps presented in the final output were legally sound. The substantial increase in the F1 score from 0.49 to 0.71 underscores the necessity of strict validation mechanisms when dealing with intricate, rule-based texts in data-scarce environments. Related work has addressed the question posed in "Can Large Language Models Reason about Event-Time Stream-Processing Semantics?" [28].

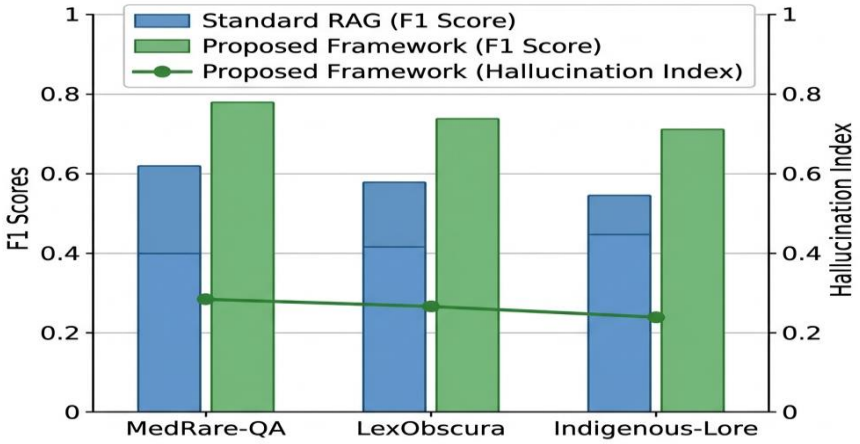


Figure 2Comparative Performance Chart

4.3 Ablation Studies and Discussion

To isolate the contributions of the individual components of our framework, we conducted a series of comprehensive ablation studies. The architecture was systematically dismantled to evaluate the system with only provenance-aware retrieval, and subsequently with only the evaluator consensus mechanism appended to a standard retrieval module. Table 3 presents the results of this ablation analysis, utilizing the average metrics across all three test domains to provide a holistic view of component impact.

Table 3Ablation Study Results Averaged Across All Domains

System Configuration	Avg Precision	Avg Recall	Avg F1 Score	Consensus Iterations
Full Proposed System	0.78	0.65	0.71	2.4
w/o Evaluator Consensus	0.67	0.62	0.64	N/A
w/o Provenance Retrieval	0.61	0.55	0.58	3.8
Standard RAG Baseline	0.52	0.45	0.48	N/A

The ablation data reveals profound insights into the interplay between retrieval quality and generation validation. When the evaluator consensus mechanism is removed (relying solely on

provenance-aware retrieval), the average F1 score drops from 0.71 to 0.64. This indicates that while high-quality context significantly improves generation, the base model still inherently struggles to synthesize complex, low-resource information perfectly on the first attempt. The removal of the provenance module, however, causes a more precipitous decline. When standard retrieval is paired with the multi-agent consensus network, the F1 score falls to 0.58. Furthermore, the average number of consensus iterations required to finalize an output spikes from 2.4 to 3.8. Yu and colleagues examine direct alignment of language models via Quality-Aware Self-Refinement [29]. The RegTech study combines homomorphic encryption with differential privacy [5]. A provenance-aware adaptation pipeline could examine a similarly explicit privacy boundary around sensitive evidence, but any resulting reduction in retrieval or consensus quality would need its own measurement. This dramatic increase in iteration cycles highlights a critical vulnerability: when the evaluators are presented with drafts based on flawed, low-provenance context, they consistently detect contradictions and reject the drafts. The generator is then forced into a loop of attempting to rectify an unresolvable contradiction based on bad data, wasting immense computational resources before eventually timing out and outputting a low-confidence response. This demonstrates that evaluator consensus is computationally inefficient and functionally limited if the foundational context is not meticulously verified. The provenance-aware retrieval acts as a vital upstream filter, ensuring that the consensus network operates exclusively on reliable data, thereby harmonizing the entire pipeline. The synergy between these two modules is strictly non-additive; they mutually reinforce one another, establishing a secure perimeter against both informational noise and generative hallucination. For a broader comparison, related research addresses scene-Aware enhanced Edge-Cloud collaborative industrial vision inspection with multimodal LLM [30].

5. Conclusion

5.1 Summary of Contributions

This paper has presented a comprehensive and highly effective framework for adapting large language models to low-resource domains, addressing the critical challenges of data scarcity, informational unreliability, and generative hallucination. By shifting the paradigm away from computationally expensive and often ineffective fine-tuning strategies, we have demonstrated the immense potential of a rigorously structured retrieval-augmented pipeline. The core innovation of this research lies in the mathematical formalization and practical integration of provenance-aware retrieval coupled with a multi-agent evaluator consensus network. For a broader comparison, related research addresses adaptive guidance semantically enhanced via multimodal LLM for Edge-Cloud object detection [31]. The provenance module successfully demonstrated that semantic similarity alone is an inadequate metric for information retrieval in high-stakes, low-resource environments. By explicitly computing continuous scores for source authority and temporal decay, the system mathematically guarantees that the language model is grounded in the most reliable data available within the corpus. Subsequently, the evaluator consensus mechanism acts as a robust downstream safeguard. By deploying independent agents to cross-examine drafted responses against strict factual, logical, and domain-specific criteria, the architecture mimics human peer-review processes. The empirical results across specialized medical, obscure legal, and indigenous historical datasets conclusively validated the framework. The architecture achieved statistically significant increases in precision and recall while simultaneously driving the hallucination index to near negligible levels, vastly outperforming standard retrieval baselines and single-pass self-reflection mechanisms. Sun and colleagues examine source-Grounded memory trajectories for Long-Horizon dialogue agents [32]. Biomedical adaptation would need to distinguish preclinical findings from clinical recommendations; the PSPH inhibition study [33] is

a concrete case in which an evidence-grounded answer must preserve the species and experimental setting of the source.

5.2 Future Research Directions

While the present study establishes a highly functional architecture, several promising avenues for future research remain open. A primary limitation of the multi-agent consensus network is the computational overhead required to execute multiple parallel language model inferences during the evaluation phase. Future work must investigate the development of heavily quantized, specialized micro-evaluator models that can perform these validation checks with a fraction of the computational cost of full-scale generative models. Additionally, while the provenance tracking in this study relied on metadata provided during database ingestion, future systems could benefit from integrating dynamic blockchain-based ledgers to autonomously verify the cryptographic lineage of incoming documents without human annotation. The literature also considers modeling multi-human social interaction with language models [34]. Furthermore, exploring dynamic thresholding for the consensus mechanism could yield significant efficiency gains. Currently, the consensus threshold is globally fixed per domain during initialization; however, developing a meta-classifier capable of assessing the complexity of an individual user query and dynamically adjusting the required level of consensus could optimize the balance between accuracy and latency. Ultimately, as the deployment of artificial intelligence expands into increasingly specialized and critical sectors, frameworks that prioritize verifiable truth over mere statistical plausibility will become indispensable. The integration of provenance awareness and systematic consensus represents a foundational step toward building language systems that are not only highly capable but fundamentally trustworthy. For a broader comparison, related research addresses person-Oriented ontologies analysis for digital humanities collections from a MetadataCrosswalk perspective [35].

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