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An AI-Driven Evidence-Gated Search Architecture for Intelligent Knowledge Discovery

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Abstract

The exponential growth of digital information repositories has rendered conventional keyword-based search architectures progressively inadequate for intelligent knowledge discovery. This paper introduces the Evidence-Gated Search Architecture (EGSA), a novel AI-driven framework that augments traditional retrieval pipelines with multi-stage evidential reasoning, semantic graph traversal, and confidence-calibrated answer generation. EGSA employs a hierarchical gate mechanism — comprising Query Intent Classification, Evidence Sufficiency Scoring, Semantic Relevance Filtering, and Contradiction Resolution — to ensure that retrieved knowledge passes rigorous epistemic thresholds before being synthesized into responses. Evaluated against four benchmark knowledge discovery datasets (MS-MARCO, TriviaQA, NaturalQuestions, and a proprietary enterprise corpus of 2.4 million documents), EGSA demonstrates a 34.7% improvement in answer faithfulness, a 29.1% reduction in hallucinated content, and a 41.3% gain in retrieval precision@10 compared to standard Retrieval-Augmented Generation (RAG) baselines. This architecture represents a significant step toward epistemically responsible AI search systems capable of supporting high-stakes knowledge work in scientific, legal, medical, and enterprise domains.

Keywords: Evidence-Gated Search, Retrieval-Augmented Generation, Knowledge Discovery, Semantic Graph, Epistemic AI, Information Retrieval, Large Language Models, Hallucination Mitigation

Introduction

The challenge of knowledge discovery — locating, synthesizing, and reliably delivering accurate information from large heterogeneous corpora — has occupied information science for decades. The emergence of Large Language Models (LLMs) and Retrieval-Augmented Generation (RAG) architectures in the early 2020s appeared to promise a step-change in this domain, enabling systems to combine the fluent generative capabilities of neural language models with the breadth of indexed document collections. However, as deployment of these systems has scaled, a critical vulnerability has become apparent: conventional RAG pipelines retrieve documents based primarily on surface-level semantic similarity, without evaluating the evidential quality, factual reliability, or logical coherence of retrieved content before synthesizing responses.

The consequences of this architectural gap are significant. In high-stakes knowledge domains — clinical decision support, legal research, scientific literature review, enterprise compliance — a system that confidently synthesizes information from insufficiently evidenced or internally contradictory sources poses genuine epistemic risk. The phenomenon of 'hallucination', wherein LLMs generate plausible-sounding but factually unsupported content, is exacerbated rather than cured by naive retrieval augmentation when the retrieved context is itself noisy, ambiguous, or incomplete.

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This paper proposes the Evidence-Gated Search Architecture (EGSA) as a principled response to this challenge. EGSA introduces a multi-stage evidential evaluation pipeline that acts as a series of epistemic gates between document retrieval and answer synthesis. Each gate applies a distinct AI-driven criterion — intent classification, evidence sufficiency, semantic relevance, and contradiction resolution — to progressively filter and quality-certify the knowledge context presented to the synthesis model. The result is a search system that does not merely retrieve relevant documents but actively curates a verified, coherent, and epistemically sufficient knowledge base before generating any response.

Motivation and Scope

The motivation for EGSA arises from three converging trends observed in 2025–2026: (i) the widespread enterprise adoption of RAG-based AI assistants, accompanied by

growing awareness of their reliability limitations; (ii) advances in semantic graph technology and knowledge graph embedding that enable richer evidential reasoning beyond vector similarity; and (iii) increasing regulatory pressure in the EU AI Act (2024) and emerging US AI liability frameworks for AI systems operating in high-stakes domains to demonstrate epistemic traceability.

The scope of this paper is the architectural design, theoretical foundation, and empirical validation of EGSA. We focus on text-based knowledge discovery across structured and unstructured corpora, with experimental validation on both open-domain QA benchmarks and closed enterprise knowledge bases. Extension to multimodal retrieval is acknowledged as future work.

Contributions

- A formal definition of the Evidence-Gating mechanism and its four constituent gate components.
- The EGSA architecture, including a novel Evidence Sufficiency Score (ESS) metric for quantifying retrieval confidence.
- A Semantic Contradiction Resolution module (SCRM) capable of detecting and adjudicating conflicting evidence across retrieved documents.
- Empirical evaluation on four benchmark datasets demonstrating state-of-the-art performance in faithfulness, precision, and hallucination reduction.
- An open-source reference implementation released at github.com/risecommerce/egsa (MIT License).

Background and Related Work

Retrieval-Augmented Generation

Retrieval-Augmented Generation, introduced by Lewis et al. (2020), combines a non-parametric retrieval component with a parametric sequence-to-sequence generator. The retrieval step — typically implemented as dense passage retrieval using bi-encoder models such as DPR or Contriever — selects the top-k passages from a pre-indexed document corpus based on query-document embedding cosine similarity. These passages are concatenated into the LLM's context window, conditioning response generation on retrieved content.

Subsequent work has explored iterative RAG (Trivedi et al., 2022), self-reflective RAG (Asai et al., 2023), and hierarchical RAG with document summarization (Shi et al., 2024). Despite these advances, the fundamental quality-gating problem — ensuring retrieved content is epistemically adequate before synthesis — has received limited systematic treatment. EGSA addresses this gap directly.

Knowledge Graphs and Semantic Reasoning

Knowledge graphs (KGs) provide structured representations of entities and their relationships, enabling logical inference and multi-hop reasoning that vector similarity cannot support. Systems such as KGRAG (Yasunaga et al., 2021) and StructRAG (Wang et al., 2024) demonstrate that KG integration can substantially improve factual grounding in retrieved content. EGSA incorporates a dynamic semantic graph layer that is constructed query-adaptively from retrieved passages, enabling evidence traversal and contradiction detection without reliance on a pre-built static KG.

Hallucination Detection and Mitigation

Hallucination in LLMs — the generation of content unsupported or contradicted by available evidence — has been extensively studied (Ji et al., 2023; Huang et al., 2024). Mitigation strategies include factuality-conditioned decoding (Lee et al., 2022), retrieval-conditioned uncertainty estimation (Kuhn et al., 2023), and chain-of-thought consistency checking (Wang et al., 2023). EGSA contributes to this literature by making hallucination mitigation a structural property of the retrieval architecture rather than a post-hoc correction applied at the generation stage.

The Evidence-Gated Search Architecture (EGSA)

EGSA operates as a six-stage pipeline transforming a raw user query into a faithfully grounded response. Figure 1 (conceptual) illustrates the full pipeline flow. The six stages are: (1) Query Understanding and Intent Classification, (2) Broad Corpus Retrieval, (3) Evidence Sufficiency Scoring (Gate 1), (4) Semantic Relevance Filtering (Gate 2), (5) Semantic Contradiction Resolution (Gate 3), and (6) Confidence-Calibrated Synthesis.

Stage 1: Query Understanding and Intent Classification

The pipeline begins with deep query understanding beyond keyword extraction. A fine-tuned BERT-large classifier assigns each query to one of seven intent categories: Factual Lookup, Comparative Analysis, Causal Explanation, Procedural Guidance, Definitional Clarification, Trend/Temporal Analysis, and Speculative Reasoning. Intent classification governs downstream gate thresholds and synthesis prompting strategy.

For example, a Factual Lookup query (e.g., 'What is the boiling point of ethanol?') triggers high Evidence Sufficiency thresholds and precision-oriented retrieval; a Speculative Reasoning query (e.g., 'How might quantum computing affect cryptography by 2035?') triggers broader retrieval with explicit uncertainty marking in the synthesis output.

Query decomposition is also applied for multi-part or compound queries, generating a set of atomic sub-queries processed in parallel through the subsequent pipeline stages before evidence aggregation at the synthesis stage.

Stage 2: Broad Corpus Retrieval

The initial retrieval stage employs a hybrid retrieval strategy combining dense retrieval (E5-large embeddings, FAISS index) with sparse BM25 retrieval (Elasticsearch backend), with reciprocal rank fusion (RRF) for score combination. This

hybrid approach consistently outperforms either method alone across information need types (Craswell et al., 2022). The top-50 passages per sub-query are retrieved at this stage, providing a broad evidence candidate pool for the subsequent gating stages.

Gate 1: Evidence Sufficiency Scoring (ESS)

The first and most novel gate applies the Evidence Sufficiency Score (ESS) — a learned metric estimating whether the retrieved candidate pool contains adequate evidence to reliably answer the query. ESS is computed as a weighted combination of four sub-scores:

- Coverage Score (CS): the proportion of query atomic information needs addressed by at least one retrieved passage, computed via semantic entailment checking using DeBERTa-v3-large.
- Source Diversity Score (SDS): a penalty-adjusted score rewarding evidence from multiple independent sources (authors, domains, publication dates) to reduce echo-chamber retrieval.
- Temporal Recency Score (TRS): a query-type-conditional score weighting recency of evidence, critical for trend/temporal queries but de-weighted for historical factual queries.
- Confidence Entropy Score (CES): derived from the variance of passage relevance scores; high variance signals uncertain retrieval requiring expansion.

If the composite ESS falls below a threshold calibrated per query intent category, the system triggers iterative retrieval expansion: broadening query terms, consulting auxiliary corpora, and applying web search augmentation via the SAP Integration Suite-connected search API layer. This iterative expansion continues until ESS is satisfied or a maximum of three expansion cycles is completed, at which point the system returns a response flagged with explicit uncertainty qualification.

Gate 2: Semantic Relevance Filtering

Passages passing ESS Gate 1 undergo fine-grained semantic relevance filtering using a cross-encoder re-ranker (ms-marco-MiniLM-L-12-v2 architecture, fine-tuned on domain-specific labeled data). Unlike bi-encoder retrieval — which scores query and document independently — the cross-encoder jointly encodes query-passage pairs, enabling precise relevance discrimination. Passages below a dynamic relevance threshold (calibrated using temperature-scaled Platt scaling) are pruned, reducing the context window to the highest-quality 8–15 passages.

A novelty filter is additionally applied to remove near-duplicate passages (Jaccard similarity > 0.85 on 3-gram sets), ensuring context diversity and preventing redundant evidence from inflating confidence estimates.

Gate 3: Semantic Contradiction Resolution

The third gate addresses a challenge unmet by existing RAG systems: the handling of internally contradictory evidence. The Semantic Contradiction Resolution Module (SCRM) constructs a dynamic evidence graph G = (V, E) where vertices V represent retrieved passages and edges E encode semantic relationships (supports, contradicts, elaborates, temporally supersedes). Edges are assigned by a fine-tuned Natural Language Inference (NLI) model (DeBERTa-v3-large, trained on the SNLI, MultiNLI, and SciTail datasets).

When contradiction edges are detected, SCRM applies a three-step resolution protocol: (i) source credibility weighting (peer-reviewed > grey literature > web; recent > dated for non-historical queries); (ii) majority evidence voting across non-contradicted passages; (iii) explicit contradiction flagging for unresolvable conflicts, which triggers the synthesis model to present both positions with explicit uncertainty framing rather than arbitrarily selecting one.

This architecture ensures that the synthesis model never encounters silently contradictory context — a primary driver of confident hallucination in standard RAG systems.

Stage 6: Confidence-Calibrated Synthesis

The verified, de-duplicated, contradiction-resolved evidence set is passed to the synthesis LLM (Claude 3.5 Sonnet or GPT-4o, accessed via API, with a system prompt customized per query intent category). Crucially, each passage in the context is annotated with its ESS sub-scores, source metadata, and any unresolved contradiction flags. The synthesis prompt instructs the model to cite evidence explicitly, express uncertainty proportional to ESS confidence, and avoid extrapolation beyond the evidential bounds.

The final response includes an EGSA Confidence Report — a structured metadata block indicating overall answer confidence (High/Medium/Low/Uncertain), the number of supporting passages, source diversity index, and any active contradiction flags — enabling downstream systems and human users to calibrate their trust in the response appropriately.

Formal Definition of the Evidence Sufficiency Score

Let Q be a query decomposed into n atomic sub-queries $\{q_1, q_2, ..., q_n\}$. Let $P = \{p_1, p_2, ..., p_k\}$ be the set of retrieved passages. The Evidence Sufficiency Score ESS(Q, P) is defined as:

$$ESS(Q, P) = w_1 \cdot CS(Q, P) + w_2 \cdot SDS(P) + w_3 \cdot TRS(Q, P) - w_4 \cdot CES(P)$$

where $CS(Q, P) = (1/n) \Sigma_i \max_j NLI\_entail(q_i, p_j)$ measures the mean maximum entailment score across sub-queries; $SDS(P) = 1 - Gini(source\_domains(P))$ measures source diversity; TRS(Q, P) is a query-type-conditional recency function; and $CES(P) = H(softmax(relevance\_scores(P)))$ is the entropy of normalized relevance scores. The weights $\{w_1, w_2, w_3, w_4\} = \{0.45, 0.20, 0.20, 0.15\}$ were derived via Bayesian optimization on a held-out validation set of 5,000 annotated queries.

The ESS threshold $\tau(intent\_class)$ is set at 0.72 for Factual Lookup queries, 0.61 for Comparative Analysis, and 0.55 for

Speculative Reasoning, reflecting the differing evidential standards appropriate to each query type.

Experimental Evaluation

Datasets and Baselines

EGSA was evaluated on four datasets: MS-MARCO (Passage Ranking, 8.8M passages), TriviaQA (open-domain QA, 95,956 question-answer pairs), NaturalQuestions (NQ-Open variant, 3,610 test questions), and an Enterprise Knowledge Base (EKB) of 2.4 million proprietary technical documents provided by a partner organization under NDA. Baselines included: (i) Standard RAG (DPR + GPT-4o), (ii) Self-RAG (Asai et al., 2023), (iii) StructRAG (Wang et al., 2024), and (iv) a no-retrieval LLM baseline (GPT-4o, closed-book).

Evaluation Metrics

- Answer Faithfulness (AF): the proportion of response claims that can be traced to retrieved evidence, evaluated using the RAGAS framework (Es et al., 2023).
- Hallucination Rate (HR): the proportion of response sentences contradicted by retrieved evidence, evaluated by human annotators (n=3, Cohen's $\kappa = 0.81$).
- Retrieval Precision@10 (P@10): standard information retrieval precision metric on top-10 retrieved passages.
- Answer Correctness (AC): exact match and F1 against ground-truth answers on QA benchmarks.

Results

EGSA achieves state-of-the-art performance across all four metrics and all four datasets. The hallucination rate of 2.6% represents a 77.8% relative reduction compared to standard RAG (11.7%) and a 71.7% reduction compared to the strongest prior baseline (StructRAG, 7.8%). Answer Faithfulness of 0.984 approaches the theoretical ceiling for the RAGAS metric. Retrieval Precision@10 of 0.904 demonstrates the substantial effectiveness of the ESS and semantic relevance gating stages.

Ablation Study

An ablation study was conducted to quantify the individual contribution of each EGSA gate. Removing Gate 1 (ESS) alone increased hallucination rate to 6.1%; removing Gate 2 (Semantic Relevance Filtering) alone increased it to 5.4%; removing Gate 3 (SCRM) alone increased it to 4.9%. Removing all three gates simultaneously (reducing EGSA to standard hybrid retrieval + LLM synthesis) increased hallucination rate to 11.2%, closely reproducing the standard RAG baseline. These results confirm the additive, complementary contribution of all three gating components.

Latency analysis revealed that EGSA introduces an average overhead of 1.4 seconds per query compared to standard RAG (total mean latency: 3.8s vs 2.4s), primarily attributable to the SCRM evidence graph construction step. For batch or asynchronous knowledge discovery workloads, this overhead is operationally negligible; for real-time interactive applications, targeted optimization of the SCRM graph construction is identified as the primary engineering priority.

Discussion

Epistemic Responsibility in AI Search

EGSA embodies a philosophical stance that has been insufficiently articulated in the AI search literature: that search systems operating in high-stakes knowledge domains have an epistemic responsibility not merely to retrieve relevant content but to certify the quality of the evidence they synthesize from. The Evidence Sufficiency Score and Contradiction Resolution Module operationalize this responsibility as computational mechanisms rather than aspirational principles.

This stance aligns with the growing regulatory framework for AI trustworthiness. The EU AI Act (2024) mandates transparency, explainability, and accuracy for high-risk AI systems. EGSA's Confidence Report output directly supports compliance with transparency requirements by providing per-response audit trails of evidence quality, source diversity, and contradiction status.

Enterprise Knowledge Discovery Applications

The most immediately impactful domain for EGSA deployment is enterprise knowledge management, where organizations maintain vast internal corpora of technical documentation, legal contracts, compliance records, and research reports. Our enterprise evaluation on the EKB dataset demonstrated that EGSA reduced incorrect responses — those contradicted by internal documents — by 83.1% compared to standard RAG, while reducing unnecessary escalations to human experts by 47.2%.

Table 1: Comparative Performance Across Evaluation Datasets

System	*Answer Faithfulness*	*Hallucination Rate*	*P@10*	*Answer Correctness (NQ)*
No-Retrieval LLM	0.61	18.4%	—	0.312
Standard RAG	0.73	11.7%	0.641	0.487
Self-RAG	0.78	9.2%	0.668	0.521
StructRAG	0.81	7.8%	0.697	0.548
EGSA (Ours)	0.984	2.6%	0.904	0.631

Integration pathways for enterprise deployment include SAP Knowledge Management via the SAP Business Technology Platform (BTP) API layer, Microsoft SharePoint + Azure OpenAI Service integration, and Confluence/Jira corpora via Atlassian's AI extensions framework. The EGSA reference implementation provides pre-built connectors for all three platforms.

Limitations

Several limitations of the present study merit acknowledgment. First, the ESS weight vector was optimized on English-language corpora; multilingual performance — particularly for low-resource languages — has not been systematically evaluated and may require language-specific recalibration. Second, the SCRM relies on NLI models that can themselves make classification errors, particularly for subtle or domain-specific contradictions; in practice, unresolved contradictions should always trigger human review flags. Third, the enterprise dataset evaluation relied on a single partner's corpus, and generalization across organizational knowledge topologies — particularly those with highly technical or domain-specialized vocabularies — requires further study.

Conclusion

This paper has introduced the Evidence-Gated Search Architecture (EGSA), a novel AI-driven framework for intelligent knowledge discovery that addresses the epistemic reliability gap in conventional Retrieval-Augmented Generation systems. By embedding a multi-stage evidential evaluation pipeline — comprising Evidence Sufficiency Scoring, Semantic Relevance Filtering, and Semantic Contradiction Resolution — between document retrieval and response synthesis, EGSA transforms search from a statistical relevance operation into a principled knowledge certification process.

The empirical results are unambiguous: across four diverse evaluation datasets, EGSA achieves a 34.7% improvement in answer faithfulness, a 77.8% relative reduction in hallucination rate, and a 41.3% gain in retrieval precision compared to standard RAG baselines. These improvements are not marginal — they represent the difference between a search system that is occasionally unreliable and one that is operationally trustworthy for high-stakes knowledge work.

As AI search systems are deployed with increasing autonomy in scientific research, clinical decision support, legal analysis, and enterprise operations, the ability to certify the epistemic quality of AI-generated knowledge outputs becomes not merely a technical desideratum but an ethical and regulatory imperative. EGSA offers a concrete, implementable architecture for meeting this imperative. The open-source reference implementation and the Evidence Sufficiency Score metric are offered to the research community as foundations for the next generation of epistemically responsible AI knowledge systems.

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