CLEAR: Contamination-Aware Evaluation of Retrieval in Agentic Fact-Checking

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Abstract

Evaluating information retrieval in agentic systems is increasingly difficult due to model contamination and tight coupling between retrieval and agent reasoning. Large language models (LLMs) may recall fact-checking knowledge from pretraining, while agents shape queries in ways that confound retrieval evaluation, causing standard end-to-end evaluations to yield conclusions that do not generalize across agentic architectures or datasets. We introduce a contamination-aware evaluation framework for retrieval in agentic fact-checking that fixes the language model and corpus while varying retrievers, datasets, and agentic architectures. This design enables controlled analysis of how model-side contamination and agent-induced query generation affect retrieval quality under a consistent knowledge prior. Our experiments show that contamination affects retrieval behavior and that retriever rankings are unstable across agentic architectures. For datasets with incomplete evidence annotations, where document-level retrieval metrics provide only a limited signal, we propose nDEv2R, a rank-sensitive fact-level retrieval metric. While instantiated in fact-checking, our findings apply more broadly to evaluating retrieval components embedded in agentic systems such as question answering and multi-document reasoning.

1 Introduction

Misinformation undermines trust in democratic processes, science, and institutions, contributing to poor decision-making with harmful real-world consequences (Zarocostas, 2020). Large language models (LLMs) amplify this problem through hallucinations or deliberate misuse to generate disinformation at scale (Augenstein et al., 2024; Wang et al., 2025). Since the volume of misinformation now exceeds human fact-checking capacity, automated fact-checking (AFC) has become essential (Vlachos and Riedel, 2014). Following journalistic practices, AFC systems retrieve relevant evidence and ground their verdicts in it (Guo et al., 2022). This evidence-based approach enhances transparency, trust, and accountability, critical factors for responsible real-world deployment (Nakov et al., 2021; Warren et al., 2025).

Despite the central role of evidence collection in both journalistic and automated fact-checking (Arnold, 2020), retrieval methods for AFC remain understudied. Recent AFC architectures use agentic designs that decompose claims into subclaims or questions and retrieve evidence using drop-in search engines, often commercial ones (Xie et al., 2025; Braun et al., 2025; Vladika et al., 2025). While such designs improve evidence coverage, they complicate evaluation: retrieval performance becomes entangled with the agent's reasoning and decomposition strategies, making fair comparisons across methods nearly impossible. Data contamination poses an additional challenge. LLMs may memorize information from pretraining (Sainz et al., 2023), allowing them to recall why claims are incorrect and generate useful subqueries or subquestions while bypassing the typical difficulties of formulating queries from novel claims alone to find evidence (Glockner et al., 2022). Commercial search engines exacerbate this issue by prioritizing verified fact-checking articles (Koronska and Rogers, 2024), further simplifying the task for previously fact-checked claims. Moreover, dependence on commercial search engines limits the applicability of fact-checking systems in domains involving sensitive or non-public data, as is common in enterprise settings (Bruckhaus, 2024). Disentangling retrieval methods from modern agentic systems is therefore an important yet understudied research direction.

We investigate two research questions:

- **RQ1:** Does model-side contamination af-

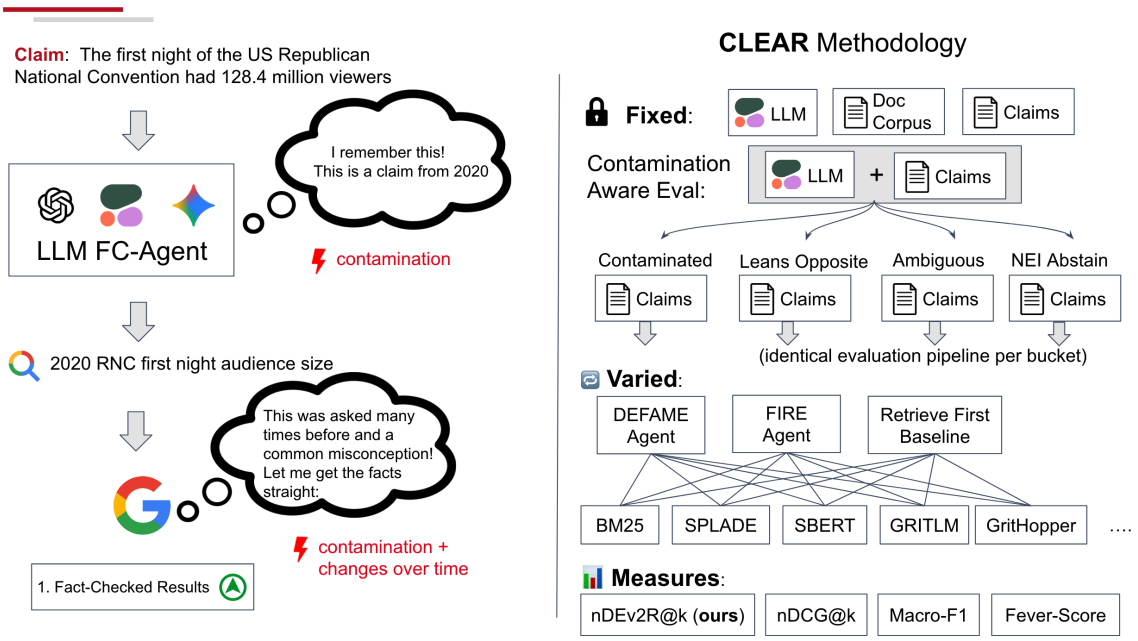

Figure 1: Overview of the CLEAR methodology. **Left:** In realistic fact-checking settings, contamination can arise from both language models and external search engines: LLMs may recall claims from pretraining, while search results can change over time and favor previously fact-checked sources. **Right:** CLEAR enables controlled evaluation by fixing the LLM, document corpus, and claims, and stratifying claims via LLM-only probing into contamination categories. Each category is evaluated using an identical pipeline while varying agent architectures and retrieval methods, allowing analysis of agent-retriever interaction effects using standard metrics and our proposed nDEv2R@k.

fect evidence retrieval performance on fact-checking datasets?

- **RQ2:** Is evidence retrieval performance independent of the surrounding agentic system once the LLM and corpus are fixed?

To answer these questions, we present CLEAR (Contamination-aware Longitudinal Evaluation of Agentic Retrieval), a contamination-aware evaluation methodology comprising three diverse single- and multi-hop fact-checking datasets for evaluating the interaction between retrieval methods and agent-based fact-checking systems. We design CLEAR to examine how retrieval method choices across different agentic *architectures* affect performance in (i) selecting the correct verdict, (ii) identifying sufficient evidence, and (iii) achieving both jointly.

Studying the impact of retrieval on fact-checking requires controlling for the LLM's internalized knowledge. Different LLMs may encode different amounts of evidence during pretraining and may therefore rely on retrieval to different degrees for the same claim. Comparing retrieval methods across changing models would thus not provide an apples-to-apples evaluation: performance differences could reflect either retrieval quality or differences in the model's prior knowledge. We therefore fix the underlying LLM across all main experiments, estimate contamination through its evidence-free verdict behavior, and evaluate retrieval methods and agentic architectures conditioned on the resulting contamination levels across multiple benchmarks. This keeps the model's knowledge prior constant and enables controlled comparisons across retrievers and agents. We later validate that selected interaction effects persist under additional LLM backbones, while keeping the fixed-LLM setup as the main protocol for controlled attribution.

Our experiments show that retrieval performance is highest for ambiguous claims, where the fixed LLM does not produce a stable evidence-free verdict, and lower for both contaminated and leans-opposite claims, where the model exhibits confident prior beliefs (RQ1). This suggests that agentic systems retrieve better evidence when the LLM's parametric knowledge alone is insufficient for fact-checking. We further find that retriever rankings are not stable across agentic workflows: the same retriever can perform differently depending on how

Dataset	Contaminated	Ambiguous	Leans Opposite	NEI-Abstain	Number of Claims
EX-Fever	27.0%	33.4%	11.8%	27.8%	500
AveriTeC	33.0%	18.8%	14.8%	33.4%	500
SciFact	35.3%	30.3%	10.9%	23.5%	279

Table 1: Contamination categories derived from 10 predictions per claim without providing evidence. A claim is marked contaminated when the model reproduces the gold label in at least nine samples; leans false when it matches once or never; ambiguous otherwise; and NEI-Abstain when the model answers NOT ENOUGH INFO in at least nine samples.

the system formulates queries, iterates over evidence, and decides when to stop retrieving (RQ2). These dependencies hinder the independent development and evaluation of new retrieval techniques and confound performance attribution, making it difficult to isolate the impact of specific design choices. CLEAR exposes these dependencies and provides a modular protocol for evaluating retrieval methods across agentic workflows.

2 CLEAR: Contamination-aware Longitudinal Evaluation of Agentic Retrieval

We design CLEAR around four principles: (i) end-to-end evaluation with retrieval in the loop; (ii) modularity to swap retrievers and AFC architectures; (iii) reproducibility via fixed corpora, prompts, and retrieval interfaces; and (iv) coverage across single- and multi-hop claims.

2.1 CLEAR Method

The goal of CLEAR is to evaluate the performance of retrieval methods used by agentic fact-checking systems. We define an agentic fact-checking system as any LLM-based system that collects evidence documents and reasons over them to produce a veracity label. The agent may either pass the original claim directly to the retrieval component, as in traditional fact-checking pipelines (Thorne et al., 2018; DeHaven and Scott, 2023), or first decompose claims into sub-claims or questions (Ousidhoum et al., 2022; Chen et al., 2024a). We define the evidence retrieval task as follows: Given a claim c and a retrieval method R integrated into an agentic fact-checking system F, the retrieval method R must identify the correct and complete set of evidence documents to enable the fact-checking system F to make the veracity prediction. Our task definition is intentionally conditioned on a fixed set of fact-checking systems with a fixed LLM, allowing us to systematically evaluate the retrieval method's capabilities across diverse yet representative claim decomposition strategies when integrated into an agentic system, while accounting for potential data contamination when the LLM has previously encountered information about a claim during pretraining (Sainz et al., 2023).

Isolating the impact of individual design choices in modern AFC systems is intractable. We therefore operate under two assumptions: First, the AFC system is not tied to a specific retrieval method, allowing retrieval components to be replaced and evaluated independently (*retrieval independence*). Second, the AFC system is not tied to a specific LLM, enabling systematic analysis of contamination effects by fixing the underlying model (*LLM independence*). Both assumptions should hold for general AFC systems that support independent incorporation and improvement of retrieval and LLM components, which is the focus of this study.

2.2 CLEAR Instantiation

We instantiate CLEAR with three fact-checking agents, three datasets, and seven retrievers, which we outline in the following sections. To study contamination effects in a controlled setting (RQ1), we fix the underlying language model across all main experiments, as model-side contamination depends directly on the LLM's pretraining exposure and parametric knowledge. We use `Command-A` from Cohere (Cohere et al., 2025) for all agents and datasets. In addition, we use Qwen3-8B and Qwen3-32B (Yang et al., 2025) for auxiliary analyses of model-specific contamination and agent-retriever interaction effects. We discuss hyperparameters in Appendix F. Our code is anonymized and publicly available at `https://anonymous.4open.science/r/CLEAR-B03C`.

2.3 Datasets

We select three text-based fact-checking datasets that cover complementary retrieval regimes relevant to agentic fact-checking. **SciFactOpen** targets high-precision retrieval for scientific claims using

Model	Contam.	Ambig.	Leans Opp.	NEI
Command-A	33.0%	18.8%	14.8%	33.4%
Qwen3-32B	38.2%	36.2%	22.2%	3.4%
Qwen3-8B	37.0%	28.8%	23.4%	10.8%

Pair	Spearman ρ
Qwen3-32B $\leftrightarrow$ Qwen3-8B	0.737^{***}
Qwen3-32B $\leftrightarrow$ Command-A	0.433^{***}
Qwen3-8B $\leftrightarrow$ Command-A	0.356^{***}

Table 2: Left: contamination categories for AveriTeC (500 claims per model). Right: pairwise Spearman ρ between contamination splits ($^{***}p<0.001$). The Qwen models agree strongly with each other but disagree with Command-A, confirming contamination is model-specific.

evidence from research abstracts (Wadden et al., 2022). **AveriTeC** contains real-world claims from news and the web with long, heterogeneous documents and silver, incomplete evidence supervision (Schlichtkrull et al., 2023). **Ex-FEVER** provides a controlled multi-hop setting over Wikipedia, where claims require aggregating evidence across multiple documents (Ma et al., 2024). Together, these datasets span single- and multi-hop retrieval, gold and silver supervision, and diverse corpus characteristics. Dataset-specific preprocessing and adaptations to our retrieval-centric setup are described in Appendix A.

2.4 Contamination Analysis

For every claim we compare the sampled verdicts to the gold label and assign the claim to one of four buckets:

- **Contaminated**: the model outputs the gold verdict in at least nine of ten runs. This is a behavioral proxy for confident verdict prediction without evidence, not a direct measurement of memorization.
- **Leans Opposite**: the gold verdict appears zero or one times, indicating the model consistently predicts an incorrect label.
- **Ambiguous**: the gold verdict appears two to eight times; the model is inconsistent, so we treat the claim as uncertain rather than clearly contaminated.
- **NEI-Abstain**: the model answers NOT ENOUGH INFO in nine or more runs. We do not mark such cases as contaminated because the model explicitly refuses to commit. Claims whose gold label is NOT ENOUGH INFO are never marked contaminated: they are assigned to NEI-Abstain, Leans Opposite, or Ambiguous depending on the prediction distribution.

Although this contamination estimate is approximate, this limitation does not affect the role of the buckets in our study: factors other than memorization may enable correct evidence-free predictions, but both memorization and other forms of prior knowledge reduce the model's reliance on retrieved evidence. We therefore interpret the buckets as evidence-reliance categories rather than direct memorization labels. The nine-out-of-ten threshold is intentionally conservative: it reduces sensitivity to stochastic decoding noise and avoids treating occasional correct guesses as evidence-independent behavior. We use it to obtain a reliable partition for controlled retrieval evaluation rather than to directly measure memorization.

Table 1 reports the resulting distribution. The EX-Fever subset shows moderate contamination: 27.0% of the claims are solved perfectly without retrieval, with the largest share (33.4%) falling into the ambiguous category and 27.8% leading to NEI responses. AveriTeC (500 claims) shows a similar pattern: one third contaminated (33.0%), one third NEI responses (33.4%), with ambiguous and leaning-false claims comprising the remainder. SciFact exhibits the highest contamination rate at over one third (35.3%), with substantial ambiguous (30.3%) and NEI-abstain (23.5%) shares, underscoring how the model handles specialized biomedical knowledge with varying degrees of certainty. We use these buckets to stratify subsequent analyses and to measure whether retrieval remains helpful once uncontaminated claims are isolated.

Table 2 assesses how evidence-reliance categories change across LLMs. We recompute the contamination splits for AveriTeC using Command-A, Qwen3-32B, and Qwen3-8B. The resulting distributions differ substantially across model families: the two Qwen models agree more strongly with each other than with Command-A, while agreement between Command-A and the Qwen models is much weaker. This confirms that contamination is not a dataset-intrinsic property alone, but depends on the model's parametric knowledge and calibration. Consequently, changing the LLM changes the evidence-reliance partition itself, so cross-LLM comparisons conflate retrieval quality with differences in the model's prior knowledge. We therefore fix a single LLM in the main experi-

ments to preserve controlled attribution when evaluating the interplay between agentic architectures and retrieval methods, and use additional LLMs only as auxiliary robustness analyses.

2.5 AFC Architectures

In CLEAR, we evaluate retrieval methods within three representative AFC architectures. As a baseline, we use a vanilla retrieve-first model that directly passes the claim to a retriever and verifies it using the top-k retrieved documents. As agentic AFC systems, we adopt DEFAME (Braun et al., 2025) and FIRE (**?**), two state-of-the-art approaches that iteratively generate subqueries, maintain a running evidence state, and output a veracity label only after sufficient evidence has been collected. Both systems come with their specific design choices and prompts, which we keep as-is to preserve their original behavior and avoid adaptation to specific retrieval methods.

2.6 Retrieval Methods

Following current surveys on retrieval-augmented systems (Chen et al., 2024b; Fan et al., 2024; Gao et al., 2023), we select representative retrievers from sparse, dense, late-interaction, and multi-hop retrieval. We include BM25 (Robertson and Zaragoza, 2009) and SPLADE (Formal et al., 2021) as sparse lexical methods; Sentence Transformers (Reimers and Gurevych, 2019), Contriever (Izacard et al., 2022), and GritLM (Muennighoff et al., 2024) as dense bi-encoder retrievers; ColBERTv2 (Santhanam et al., 2022) as a late-interaction model; and GritHopper (Erker et al., 2026) as a multi-hop retriever.

All methods are used off-the-shelf without additional fine-tuning to ensure that differences in performance reflect their general capabilities and how they interact with agentic fact-checking pipelines rather than task-specific adaptation.

2.7 Metrics

Two common approaches exist for evaluating evidence in fact-checking. The first (*reference-based*) assumes knowledge of which documents or information are needed to predict the veracity label (Thorne et al., 2018; Aly et al., 2021; Schlichtkrull et al., 2023), enabling strict evaluation but presuming a single path to the correct label. The second (*veracity-based*) assesses evidence quality indirectly via the veracity prediction, offering more flexibility but unable to detect predictions made with insufficient evidence (Akhtar et al., 2026). In this work, we consider both complementary approaches and report the following metrics. For veracity-based metrics, we report Macro F_1.

Gold references On datasets with complete gold evidence annotations, we evaluate retrieval using nDCG@10 as a reference-based metric. For each claim, we align each gold document to the retrieval iteration where it achieved its best (lowest) rank, then compute sample-level nDCG@10 aggregated across all gold documents. This *gold-document-oriented* aggregation measures whether the agent eventually retrieves relevant evidence, but it favors multi-hop agents that perform many retrieval attempts. To account for retrieval cost, we additionally compute a hop-regularized variant that divides the gold-document-oriented nDCG by the logarithm of the number of retrieval iterations plus one ($\text{nDCG@10}/\log(\text{hops}+1)$), which we find correlates most strongly with veracity prediction. We explore additional aggregation strategies in Appendix E.

Silver references In more realistic open world tasks like AveriTeC (Schlichtkrull et al., 2023), where evidence annotations are incomplete or silver, this assumption no longer holds. Multiple documents may express overlapping or partial factual support, and useful evidence may not be explicitly annotated as gold. In such settings, document-level relevance metrics become brittle, as binary judgments fail to capture degrees of factual support. Ev2R (Akhtar et al., 2026) addresses this limitation by evaluating evidence at the fact level using LLMs, computing a F_1 score based on factual overlap between retrieved documents and reference evidence. While this provides a more informative signal than binary document relevance, Ev2R evaluates documents in isolation and does not account for the ranked nature of retrieval. This is limiting in agentic fact-checking systems, where retrieval outputs are consumed as ordered lists and rank strongly influences downstream usage across different agent architectures .

We therefore propose **nDEv2R@k** (normalized discounted Ev2R), a rank-sensitive extension of Ev2R that evaluates retrieval quality as an ordered list of documents. Let $\mathcal{G} = \{g_1, \ldots, g_m\}$ denote the set of gold evidence documents for a claim, and let d_i be the retrieved document at rank i. We

define

$$\text{nDEv2R@k} = \frac{\sum_{i=1}^{k} \frac{\text{Agg}_{g \in \mathcal{G}} \text{Ev2R}(d_i, g)}{\log_2(i+1)}}{\sum_{i=1}^{k} \frac{1}{\log_2(i+1)}},$$

where Agg aggregates fact-level overlap scores across the gold evidence set. In our experiments, we instantiate Agg as either a maximum, reflecting a sufficiency-based assumption where one informative gold document is enough (similar to the Feverscore), or as a mean, reflecting coverage over all annotated gold documents. This yields an nDCG-style metric that is rank-sensitive, bounded in $[0, 1]$, and captures how early factual evidence appears in the retrieved ranking rather than whether the final verdict is correct. In our analysis, we therefore treat nDEv2R@k as a pure retriever-quality measure and contrast it against unweighted Ev2R aggregations to isolate the effect of ranking.

3 Contamination Impact on Retrieval

We begin by analyzing how model-side contamination affects both veracity prediction and evidence retrieval (RQ1). Using the contamination categories defined in Section 2.4, we stratify all results into contaminated, leans-opposite (uncontaminated), and ambiguous/NEI-abstain claims. This stratification allows us to separate cases where the underlying language model likely recalls the correct verdict from pretraining from cases where the claim must be resolved primarily through retrieved evidence.

Category	Macro F1	NDCG@10	LogNDCG@10
Overall	50.08	32.07	34.91
Contaminated	54.06	30.25	33.06
Leans Opposite	45.38	30.01	32.82
Ambiguous	49.00	33.57	36.43

Table 3: Overall performance by contamination category averaged across all agents and datasets (tri-label scheme, selected runs). NDCG@10 uses gold-oriented aggregation (best rank per gold document); NDCG@10/log(h+1) accounts for retrieval efficiency.

Table 3 reports veracity prediction and retrieval quality aggregated across all agents and retrievers. As expected, veracity prediction is highest for contaminated claims (Macro F_1=54.1) and lowest for leans-opposite claims (45.4). Retrieval quality, however, follows a different pattern. Across agents, retrieval performance is highest for ambiguous claims (NDCG@10= 33.6; NDCG@10/log(h+1)= 36.4) and lower for both contaminated and leans-opposite claims (around 30 NDCG@10).

Retrieval differs only marginally between contaminated and leans-opposite claims (30.25 vs. 30.01 NDCG@10), indicating that strong internal certainty, whether correct or incorrect, does not improve retrieval. The consistently weakest retrieval on contaminated and leans-opposite claims suggests that confident internal beliefs constrain evidence exploration, consistent with confirmation bias in information seeking (Kaanders et al., 2022; Wan et al., 2025).

Taken together, these results show that retrieval performance cannot be interpreted independently of the model's internal belief state and contamination. Rather than benefiting from certainty, retrieval quality is highest when the model remains uncertain and degrades under strong internal commitment. We further analyze whether retrieved evidence corrects or reinforces the model's prior in Appendix C. In the leans-opposite split, retrieving at least one gold evidence document substantially improves label accuracy, indicating that evidence can correct initially incorrect priors. In contaminated claims, however, additional retrieved evidence can sometimes destabilize an already correct prior. This highlights the need for contamination-aware evaluation when comparing retrieval methods in agentic fact-checking systems. In the next section, we examine whether retriever rankings remain stable across different agent architectures once the language model and corpus are fixed (RQ2).

3.1 Does retrieval performance differ across different Agents?

Having established contamination-aware stratification, we now focus on why retrieval evaluation in agentic fact-checking is intrinsically difficult even under fixed LLM and corpus: agents execute *different retrieval processes* (different numbers of retrieval iterations and different stopping behavior), so standard single-shot ranking metrics become aggregation-dependent and can change the conclusions about which retriever (or agent) is "best". If not explicitly mentioned, we conduct the following experiments on all splits together except the contaminated split. For transparency we provide the main tables with contamination in Appendix H.

Gold-document metrics can favor multi-attempt agents. Iterative agents issue different numbers of retrieval iterations per claim: in our global ag-

Retriever	DEFAME			FIRE			RetrieveFirst		
	Macro-F1	logNDCG@10	nDEv2R	Macro-F1	logNDCG@10	nDEv2R	Macro-F1	logNDCG@10	nDEv2R
BM25	45.15	5.91	30.79	46.22	10.09	31.62	39.71	7.89	29.05
Contriever	27.17	1.86	10.08	39.78	3.79	10.77	27.34	4.66	12.64
GritLM	46.20	9.69	32.96	46.67	15.02	35.83	40.94	14.66	35.89
SBERT	42.34	4.91	24.68	43.66	8.02	28.79	39.37	7.68	28.45
SPLADE	44.75	7.19	28.31	45.42	9.75	29.85	37.76	10.71	30.34

Table 4: AveriTeC retrieval benchmark (Everything but Contaminated claims)

gregation, DEFAME performs 4.8 retrieval iterations on average, compared to 1.2 for FIRE (Appendix Table 17). Under gold-document-oriented nDCG@10, which records the best rank achieved by each gold document across all iterations, DEFAME slightly exceeds FIRE (38.62 vs. 36.78). This is expected because additional retrieval attempts increase the chance that each gold document appears at a good rank at least once, but it also means that the metric mixes retrieval quality with the number of attempts an agent gives itself.

Hop-regularization changes the ranking and better tracks downstream behavior. We therefore evaluate hop-regularized variants that divide gold-document nDCG@10 by a function of the number of retrieval iterations (Appendix E). This qualitatively changes the agent comparison: while DEFAME is slightly higher on unregularized nDCG@10, FIRE is substantially higher on nDCG@10/$\log(h{+}1)$ (45.90 vs. 24.81) and nDCG@10/h (30.43 vs. 10.61). We do not interpret this only as an efficiency result; rather, hop-regularization provides a retrieval signal that aligns more strongly with downstream veracity prediction. Across runs, nDCG@10/$\log(h{+}1)$ correlates more strongly with veracity than gold-oriented nDCG@10 (ρ=0.369 vs. ρ=0.282), with the clearest effect for FIRE (ρ=0.586 vs. 0.460; Appendix Table 16).

Main-table evidence: retriever rankings are agent-dependent. The three main benchmark tables already illustrate that retriever performance is not an intrinsic property of the retriever alone, but depends on the surrounding agentic process. On **SciFact** (Table 7), instruction-tuned dense retrieval is consistently strong across agents (e.g., GritLM NDCG@10: 58.48/54.08/55.39 for DEFAME/FIRE/RetrieveFirst), but the agent ordering differs across metrics and does not follow Macro-F_1 monotonically.

On **Ex-FEVER** (Table 6), FIRE+GritHopper (where we ignore the queries from FIRE and instead just use the claim together with all previous retrieved evidences for retrieval) achieves extremely high retrieval scores (NDCG@10 = 91.23), while the same dataset also shows that different agents can yield very different retrieval outcomes for the same retriever family (e.g., BM25: DEFAME NDCG@10 = 52.39 vs. FIRE = 38.66). This raises the question:

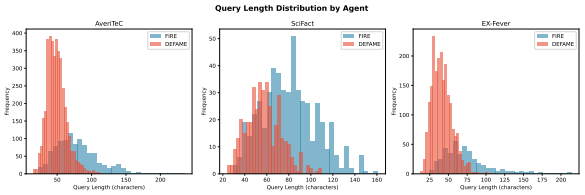

Figure 2: Query length characteristics and retriever performance. (a) Average query length by agent and dataset; FIRE produces queries 1.5–2× longer than DEFAME.

Query Length	SPLADE	GritLM	Δ
Short (<30)	55.5%	38.2%	+17.3
Long (>30)	37.8%	38.3%	-0.5

Table 5: Recall@10 by query length. SPLADE dominates short keyword-style queries, while GritLM reaches parity on longer natural-language queries.

3.2 Why Does Retrieval Differ Across Automatic Fact-Checking Systems?

Our analysis points to agent-induced query bias as a central mechanism behind unstable retriever rankings. Although DEFAME and FIRE operate on the same claims and corpus, they generate systematically different query distributions: DEFAME produces shorter keyword-style queries, whereas FIRE generates longer natural-language questions (Figure 2). These query styles interact with retriever inductive biases. Sparse retrievers such as BM25 and SPLADE benefit from short lexical queries, while dense retrievers benefit from longer semantic queries.

We verify this interaction by stratifying re-

trieval performance by query length. SPLADE strongly outperforms GritLM on short queries (55.5 vs. 38.2 Recall@10), whereas this advantage disappears on longer queries (37.8 vs. 38.3; Appendix **??**). Prompt design amplifies the same effect: replacing DEFAME's short few-shot examples with longer real-question demonstrations increases query length by 28% for Command-A and improves GritLM from 11.34 to 12.67 NDCG@10. We corroborate this trend with the Qwen models in Appendix D. The agent-level query shift also generalizes across LLMs. FIRE produces substantially longer queries than DEFAME under both Command-A (+76.3%) and Qwen3-8B (+42.9%). Thus, the interaction effects are not merely artifacts of one LLM, even though contamination partitions themselves remain model-specific. These findings show that retrieval performance in agentic fact-checking emerges from the interaction between retriever inductive biases, prompt design, and agent-specific query generation.

3.3 nDEv2R@k

For datasets with incomplete or silver evidence annotations, document-level relevance metrics provide a weak signal of retrieval quality. To address this limitation within CLEAR, we evaluate whether fact-level overlap metrics better capture the usefulness of retrieved evidence, independent of annotation completeness. In our evaluation AveriTeC is the only dataset with silver evidence annotations. In this setting, document-level relevance labels are incomplete, making gold-document NDCG@10 a weak proxy for retrieval quality. As shown in Table 8, nDEv2R@10 exhibits substantially stronger correlation with downstream veracity accuracy (Spearman $\rho = 0.23$) than gold-document NDCG@10 ($\rho = 0.095$) and unranked Ev2R aggregations (Ev2R F_1: $\rho = 0.216$), indicating that rank-sensitive fact-level evaluation provides a more informative retrieval signal under incomplete evidence supervision. While this correlation is measured against veracity prediction, we emphasize that nDEv2R@k is designed as a retrieval metric: it evaluates query and ranking quality independently of the final decision, and higher scores indicate that more relevant factual information is retrieved earlier in the ranking. We observe that the MAX aggregation is marginally more stable than MEAN, which we attribute to AveriTeC often requiring only a single decisive document for verification, though this effect may be dataset-specific.

4 Related Work

Our work complements prior evaluation work in automated fact-checking. Early FEVER-style pipelines separated document retrieval, evidence selection, and veracity prediction, enabling retrievers to be assessed independently against gold evidence annotations (Thorne et al., 2018; Hanselowski et al., 2018; DeHaven and Scott, 2023; Wadden et al., 2022). Recent agentic AFC systems instead generate intermediate questions, subclaims, or search queries before predicting a verdict, which couples retrieval with reasoning and makes end-to-end scores difficult to attribute to the retriever itself (Pan et al., 2023; Braun et al., 2025; **?**; Vladika et al., 2025). Closest to our setting are AveriTeC and Ev2R, which evaluate evidence under incomplete or silver supervision (Schlichtkrull et al., 2023; Akhtar et al., 2026); however, they do not study model-side contamination, agent-induced query shifts, or rank-sensitive fact-level retrieval. Retrieval-only benchmarks typically use predefined queries and therefore do not capture these agent–retriever interactions. We address this gap with a contamination-aware protocol for retrieval inside agentic fact-checking and extend Ev2R with nDEv2R.

5 Conclusion

We introduced CLEAR, a contamination-aware framework for evaluating retrieval in agentic fact-checking. By fixing the corpus and main LLM while varying retrievers and AFC architectures, CLEAR exposes how retrieval quality is shaped by model-side contamination, agent-specific query generation, and metric aggregation choices.

Our experiments show that retrieval performance is not an intrinsic property of the retriever alone. Contamination affects evidence seeking, retriever rankings change across agents, and gold-document metrics can favor agents that perform more retrieval attempts. For datasets with incomplete evidence annotations, we propose nDEv2R@k, a rank-sensitive fact-level metric that better captures useful evidence under silver supervision. Overall, our results suggest that retrieval in agentic systems should be evaluated neither in isolation nor purely end-to-end. Instead, it requires controlled, contamination-aware evaluation that makes agent–retriever interactions explicit.

Limitations

Our findings should be interpreted under the controlled variables of CLEAR: fixed corpora, fixed prompts, selected AFC systems, and a fixed main LLM. This design enables systematic attribution of retrieval and agent–retriever interaction effects, but it does not cover all possible model families, prompts, or agent designs. We address this with auxiliary Qwen3-8B and Qwen3-32B experiments, which show that contamination partitions are model-specific and that selected agent–retriever interaction effects persist across model backbones.

Our contamination categories are behavioral proxies based on verdict prediction without evidence. They do not directly measure memorization and do not capture finer-grained forms of contamination such as entity familiarity, partial evidence recall, or snippet-level exposure. They should therefore be interpreted as evidence-dependence categories rather than direct memorization labels.

We evaluate two state-of-the-art AFC agents, DEFAME and FIRE, together with a retrieve-first baseline. These systems cover the dominant sequential search-and-verify paradigm in current AFC, but not all agentic designs, such as ReAct-style tool use, multi-agent deliberation, or agents explicitly optimized for a specific retriever. We also keep systems close to their original implementations; thus, differences in prompts, query generation, and stopping behavior are part of the evaluated agent–retriever interaction rather than controlled away.

Finally, our gold-document nDCG aggregation records the best rank achieved across retrieval iterations, which provides an upper-bound view of eventual evidence coverage and can favor agents with more retrieval attempts. We therefore report hop-regularized variants and recommend interpreting both views together.

Ethical Considerations

This work studies retrieval behavior in agentic fact-checking systems, which inherit known ethical risks of large language models trained on large-scale data, including the propagation of societal biases and exposure to misinformation (Prakash and Lee, 2023). In addition, retrieval systems operating in open-domain settings may surface sensitive, biased, or harmful content if not carefully evaluated and controlled. Rather than deploying a new decision-making system, our work aims to improve transparency and accountability by explicitly analyzing contamination effects and evaluation pitfalls that can otherwise mask such risks. We argue that contamination-aware and controlled evaluation is a necessary step toward safer and more responsible development of retrieval-augmented and agentic NLP systems.

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A Data Preprocessing

We preprocess each dataset to ensure compatibility with our evaluation framework while preserving the original task characteristics. Table 9 summarizes the corpus sizes and document characteristics for each dataset.

Ex-FEVER. We use the Ex-FEVER dataset (Ma et al., 2024), which is built on the FEVER Wikipedia corpus snapshot. The corpus contains approximately 5.4 million documents (introductory paragraphs from Wikipedia articles). We evaluate on a stratified subset of 500 claims sampled to represent the full label distribution. For computational efficiency in initial experiments, we first evaluated 100 claims before scaling to the full 500-claim set reported in the main paper.

Retriever	DEFAME			FIRE			RetrieveFirst		
	Macro-F1	NDCG@10	logNDCG@10	Macro-F1	NDCG@10	logNDCG@10	Macro-F1	NDCG@10	logNDCG@10
BM25	51.53	52.39	31.58	60.72	38.66	43.46	40.52	54.12	78.07
Contriever	31.95	16.07	8.74	53.90	10.47	11.64	31.83	16.41	23.67
GritHopper	–	–	–	66.50	91.23	100.00	52.64	82.86	100.00
GritLM	59.11	77.10	49.30	63.05	63.13	73.58	48.67	65.75	94.85
SBERT	45.75	42.02	24.11	51.27	31.11	35.46	41.32	34.25	49.42
SPLADE	56.77	77.11	49.64	61.03	59.12	70.95	51.84	59.64	86.05

Table 6: EX-Fever 500 retrieval benchmark (Everything but Contaminated claims)

Retriever	DEFAME			FIRE			RetrieveFirst		
	Macro-F1	NDCG@10	logNDCG@10	Macro-F1	NDCG@10	logNDCG@10	Macro-F1	NDCG@10	logNDCG@10
BM25	61.76	53.36	36.00	66.35	41.65	59.92	68.45	41.54	59.93
ColBERT	56.38	48.13	29.57	69.33	35.90	51.79	62.26	36.76	53.03
Contriever	55.66	24.06	16.13	60.75	13.11	18.78	51.73	19.52	28.15
GritLM	58.79	58.48	38.03	68.04	54.08	78.02	70.12	55.39	79.92
SBERT	51.71	42.27	28.16	73.49	36.17	52.19	64.67	36.14	52.14
SPLADE	49.75	56.46	35.90	66.52	43.57	62.86	73.92	45.92	66.25

Table 7: SciFact Results (Everything but Contaminated claims)

AveriTeC. The AveriTeC dataset (Schlichtkrull et al., 2023) includes real-world claims from news and social media, paired with evidence retrieved from the web. The corpus contains approximately 4.7 million web-scraped documents with an average length of 800 characters. Unlike Ex-FEVER and SciFact, AveriTeC provides silver evidence annotations rather than gold labels, as the evidence collection process does not guarantee completeness. We use the full set of 500 test claims from the original benchmark. Due to incomplete gold evidence annotations, we report both gold-document NDCG@10 and our proposed nDEv2R@k metric for retrieval evaluation.

SciFact. The SciFact dataset (Wadden et al., 2022) focuses on scientific claim verification using evidence from biomedical research abstracts. The corpus contains 5,183 documents (PubMed abstracts) with an average length of 1,404 characters. We evaluate on 279 claims from the SciFactOpen test set. Due to the relatively small corpus size, we include ColBERTv2 (Santhanam et al., 2022) as an additional retriever for SciFact, which we exclude from the larger AveriTeC and Ex-FEVER experiments due to prohibitive indexing costs.

Retrieval Implementation. For all sparse and dense bi-encoder retrievers (BM25, SPLADE, Sentence Transformers, Contriever, GritLM), we use FAISS (Johnson et al., 2021) with exact search (`IndexFlatIP`) to ensure precise ranking. ColBERTv2 uses its native late-interaction indexing implementation. All retrievers are used off-the-shelf without task-specific fine-tuning to evaluate their general-purpose capabilities in agentic fact-checking settings.

B nDEv2R ablation

Table 10 reports correlations between retrieval metrics and veracity accuracy on AveriTeC, where gold evidence annotations are incomplete. EV2R-based metrics, which evaluate retrieval quality at the fact level rather than document level, show substantially stronger correlation with downstream veracity prediction than traditional gold-document NDCG@10. The nDEv2R@10 metric with MAX aggregation (taking the best fact overlap score against any gold document, similar to the Fever-score philosophy) achieves correlations of r=0.200 to 0.206 across agents, compared to NDCG@10's weaker correlations (r=0.028 to 0.095). This demonstrates that fact-level evaluation better captures retrieval quality when evidence annotations are incomplete or silver. NDCG@100, which considers a broader retrieval window, shows strong agent-level correlations but with limited statistical power due to fewer runs per agent.

C Evidence Retrieval and Prior Correction

We analyze whether retrieval corrects or reinforces the model's internal prior by conditioning label accuracy on whether at least one gold evidence document is retrieved in the top three results. We aggregate results across DEFAME, FIRE, and RetrieveFirst using GritLM.

The strongest effect appears in the leans-opposite split: when at least one gold document is retrieved, accuracy increases by 26.8 percent-

Metric	Spearman r	p-value
EV2R NDCG-weighted	$r = 0.230$	$p = 3.2 \times 10^{-64}$ ✓
EV2R F1 (k=10)	$r = 0.216$	$p = 8.6 \times 10^{-57}$ ✓
EV2R F1 (k=1)	$r = 0.190$	$p = 2.6 \times 10^{-44}$ ✓
NDCG@10 (gold docs)	$r = 0.095$	$p = 5.0 \times 10^{-12}$ ✓

Table 8: Correlation between retrieval metrics and veracity accuracy on AveriTeC (aggregated across all runs). EV2R-based metrics show significantly stronger correlation than gold document NDCG@10.

Dataset	Corpus Size	Avg Doc Length	# Claims
Ex-FEVER	∼5.4M	∼150	500
AveriTeC	∼4.7M	∼800	500
SciFact	5,183	1,404	279

Table 9: Dataset corpus statistics. AveriTeC and Ex-FEVER use Wikipedia-scale corpora with varying document lengths, while SciFact focuses on scientific abstracts with more uniform document sizes.

age points. This indicates that retrieval can correct initially incorrect model priors. In contrast, contaminated claims show the opposite trend, suggesting that additional evidence may sometimes introduce instability when the model already predicts the correct label without retrieval.

D Cross-Model Agent-Retriever Interaction Analysis

To assess whether the agent–retriever interaction effects observed with Command-A are specific to a single LLM, we replicate two analyses from Section 3.2 using Qwen3-8B with GritLM on AveriTeC.

Both models exhibit the same directional behavior: real-question demonstrations increase query length and improve dense retrieval effectiveness. This suggests that prompt-induced retrieval effects are not unique to Command-A.

While the magnitude differs across LLMs, both models show the same directional effect: FIRE produces substantially longer queries than DEFAME. This supports our claim that agent design induces retrieval-relevant query characteristics that persist across model backbones, even though contamination partitions themselves remain model-specific.

E NDCG Ablations Across Contamination and Agents

Iterative agentic fact-checking systems perform multiple retrieval iterations, generating several queries per claim and accumulating evidence over time. This raises a methodological question: how should retrieval quality be aggregated when agents make different numbers of retrieval attempts? It is not immediately obvious whether retrieval metrics should penalize methods that require many attempts to find relevant evidence, or whether achieving high final coverage matters regardless of the number of tries. In this section, we systematically evaluate different nDCG@10 aggregation strategies, some that focus solely on whether gold documents are eventually retrieved, and others that account for retrieval efficiency by incorporating the number of iterations required. We analyze how these strategies correlate with veracity prediction and examine agent-specific behavior across contamination splits.

E.1 NDCG Aggregation Variants

We evaluate the following nDCG@k aggregation strategies, each capturing different aspects of retrieval quality:

NDCG@10 Gold-Oriented. For each gold document, we record the best (minimum) rank achieved across all retrieval iterations, then aggregate nDCG@10 across all gold documents. This *gold-document-oriented* aggregation measures whether the agent *eventually* retrieves relevant evidence, regardless of how many attempts it takes. This strategy provides an upper bound on retrieval capability but does not distinguish between agents that find evidence efficiently versus those that require many iterations.

NDCG@10 Best Single Gold. Instead of aggregating ranks across all gold documents, we consider only the single gold document that achieves the lowest rank across all iterations. This reflects scenarios where retrieving one highly informative document is sufficient for veracity prediction, consistent with our finding that complete multi-hop evidence chains are often unnecessary.

NDCG@10 First Hop. We compute nDCG@10 using only the ranks from the *first* retrieval iteration,

Metric	DEFAME $\bar{r}$	DEFAME sig.	FIRE $\bar{r}$	FIRE sig.	RetrieveFirst $\bar{r}$	RetrieveFirst sig.
nDEv2R@10 (MAX)	0.200	✓	0.156	✓	0.206	✓
nDEv2R@10 (MEAN)	0.211	✓	0.145	✓	0.199	✓
NDCG@10 (gold docs)	0.028	×	0.091	✓	0.095	✓

✓ = most runs significant at $p < 0.05$; × = not significant

Table 10: Retrieval metric correlation with veracity accuracy by AFC architecture on AveriTeC. EV2R metrics show stronger correlation than gold-document NDCG@10.

Split	All	Hit	No Hit	Δ
Contaminated	79.5	72.9	85.7	-12.8
Leans Opposite	55.3	68.4	41.6	+26.8
Uncertain	61.6	64.1	59.4	+4.7
Overall	66.3	67.3	65.3	+2.1

Table 11: Label accuracy conditioned on whether at least one gold evidence document is retrieved in the top three results. Retrieval most strongly helps in the leans-opposite split, where the model initially predicts a label inconsistent with the gold verdict.

ignoring subsequent refinements. This isolates the quality of the initial query formulation and retrieval step, providing a lower bound on agent retrieval performance without iterative refinement.

NDCG@10 Regularized Variants. To account for the number of retrieval attempts, we divide the original nDCG@10 score by a function of the number of hops h:

- **nDCG@10 / $\sqrt{h}$**: Moderate penalty that grows sublinearly with retrieval iterations.
- **nDCG@10 / h**: Strong linear penalty proportional to the number of attempts.
- **nDCG@10 / log($h+1$)**: Gentle logarithmic penalty that grows slowly with iterations.

These regularized variants measure *retrieval efficiency*: how well an agent retrieves evidence relative to the computational cost of multiple retrieval rounds.

NDCG@10 Hop-Weighted. We assign a per-hop discount to document ranks, penalizing evidence retrieved in later iterations: effective rank $= r \times (1.0 + (h-1) \times 0.5)$, where r is the original rank and h is the hop number. This reflects the intuition that earlier retrievals are more valuable than later refinements.

NDCG@100. We compute nDCG at different cutoffs (k=10 and k=100) to assess whether retrieval quality depends on the evaluation depth. Smaller k values emphasize precision at the very top ranks, while larger k values reward broader recall.

E.2 Correlation with Veracity Prediction

To determine which nDCG variant best reflects retrieval quality for fact-checking, we compute Spearman correlations between each metric and veracity accuracy (Macro-F_1) across all runs. We analyze uncontaminated claims (leans-opposite, ambiguous, and NEI-abstain slices pooled) to focus on cases where the model must rely on retrieved evidence rather than parametric knowledge.

Table 15 reports correlations aggregated across all agents and datasets. Hop-regularized variants show substantially stronger correlations with veracity than the gold-oriented aggregation. **nDCG@10/log($h+1$)** achieves the highest correlation ($\rho = 0.369$, $p < 0.01$), followed closely by nDCG@10/$\sqrt{h}$ ($\rho = 0.368$) and the linear regularization variant ($\rho = 0.358$). This indicates that retrieval metrics that account for the number of attempts provide a more meaningful signal of retrieval quality than metrics that consider only whether gold documents are eventually retrieved.

In contrast, **nDCG@10 Best Single Gold**, which focuses on the single best-retrieved document, shows the weakest correlation. This suggests that even when one gold document is sufficient for veracity prediction, the *process* of retrieving it, including the number of attempts required, remains informative about overall retrieval quality.

E.3 Agent-Specific Correlation Analysis

We further examine whether these correlations hold consistently across different agent architectures. Table 16 reports agent-specific Spearman correlations.

For **FIRE**, hop-regularized metrics show significantly stronger correlations with veracity compared to the gold-oriented aggregation. This effect is particularly pronounced for FIRE, where nDCG@10/h achieves ρ=0.594 ($p < 0.01$), sub-

Table 12: Effect of few-shot demonstrations for DEFAME + GritLM on AveriTeC. Real-question demonstrations produce longer queries and improve dense retrieval for both LLMs.

Setting	F1	NDCG@10	Avg. Query Length
Qwen3-8B + Original few-shot	47.32	9.46	44.06
Qwen3-8B + Real-question few-shot	50.97	9.83	54.85
Command-A + Original few-shot	58.84	11.34	47.62
Command-A + Real-question few-shot	60.23	12.67	60.95

Table 13: Agent query length differences with GritLM on AveriTeC. FIRE produces longer queries than DEFAME for both LLMs.

Agent	Avg. Query Length
Qwen3-8B + DEFAME	44.04
Qwen3-8B + FIRE	62.94
Qwen3-32B + DEFAME	51.72
Qwen3-32B + FIRE	61.26
Command-A + DEFAME	44.31
Command-A + FIRE	78.13

stantially outperforming the gold-oriented metric (ρ=0.460, $p < 0.05$). For **RetrieveFirst**, correlations are moderate across metrics, with hop-regularized variants showing similar performance ($\rho \approx 0.44$, $p < 0.05$) to the gold-oriented aggregation.

In contrast, for **DEFAME**, correlations between nDCG variants and veracity are generally weaker and not statistically significant. This reflects DEFAME's tendency to over-predict the NOT ENOUGH INFO label (see confusion matrices in Appendix G), which weakens the relationship between retrieval quality and veracity accuracy for this agent. Despite stronger retrieval performance on average, DEFAME's conservative prediction strategy decouples retrieval quality from final verdict, making it difficult to detect retrieval-veracity correlations.

E.4 Agent Performance on NDCG Variants

Table 17 reports mean scores for each agent across all nDCG variants. These results reveal a striking reversal: while DEFAME outperforms FIRE on the gold-oriented aggregation, FIRE achieves substantially higher scores on all hop-regularized metrics.

On the gold-oriented nDCG@10, DEFAME scores approximately 5% higher than FIRE (38.6 vs 36.8), consistent with its multi-hop architecture retrieving gold documents at some point across multiple iterations. However, DEFAME performs approximately four to five times more retrieval iterations than FIRE on average. When retrieval quality is normalized by the number of attempts, FIRE's efficiency advantage becomes clear: on nDCG@10/log(h+1), FIRE scores nearly 85% higher than DEFAME (45.9 vs 24.8).

This pattern holds across all regularization schemes. The linear penalty (nDCG@10/h) produces the strongest effect, with FIRE scoring nearly three times higher than DEFAME, while the logarithmic penalty (nDCG@10/log($h + 1$)) yields the smallest gap but still favors FIRE substantially. Even the hop-weighted variant, which applies a moderate discount to later retrievals, shows FIRE outperforming DEFAME.

RetrieveFirst, as a single-shot baseline, performs exactly one retrieval iteration and therefore shows identical scores for the gold-oriented nDCG@10 and all hop-regularized variants (division by 1 has no effect). Its performance lies between FIRE and DEFAME on the gold-oriented metric but closer to FIRE on regularized variants, suggesting that FIRE's iterative refinement provides only modest gains over single-shot retrieval when accounting for computational cost.

Interestingly, nDCG@10 First Hop reveals that DEFAME's initial retrieval step performs comparably to FIRE's, indicating that the quality difference emerges primarily from how agents utilize iterative refinement rather than from the quality of their first queries.

E.5 Retrieval Performance Across Contamination Splits

We analyze how retrieval quality degrades when moving from contaminated to uncontaminated claims. For each agent, we compute the relative drop in nDCG@10 between the contaminated slice and the leans-opposite slice, where the model consistently predicts an incorrect label.

All agents exhibit relatively stable retrieval performance across contamination slices. DEFAME shows minimal variation (less than 1% drop in nDCG@10 from contaminated to leans-opposite

Table 14: Performance across contamination categories by agent type. NDCG@10 uses gold-oriented aggregation; NDCG@10/log(h+1) accounts for retrieval efficiency. All values are weighted by the number of claims per run.

Agent	Overall			Contaminated			Leans Opposite			Ambiguous		
	F1	NDCG	NDCG/log(h+1)	F1	NDCG	NDCG/log(h+1)	F1	NDCG	NDCG/log(h+1)	F1	NDCG	NDCG/log(h+1)
FIRE	57.3	33.7	40.4	61.3	32.1	38.3	54.7	31.9	38.9	55.8	34.9	41.9
DEFAME	49.0	31.8	20.3	54.4	29.7	19.4	44.1	29.6	19.1	47.2	33.6	21.1
RetrieveFirst	44.6	30.9	43.1	47.4	29.1	40.8	38.4	28.6	39.8	44.6	32.4	45.3

Table 15: Spearman correlation between nDCG variants and veracity accuracy across all agents (overall slice). Hop-regularized metrics correlate more strongly with veracity than the gold-oriented aggregation.

NDCG Metric	ρ	p-value
NDCG@10 / $\log(h+1)$	0.369	< 0.01
NDCG@10 / $\sqrt{h}$	0.368	< 0.01
NDCG@10 / h	0.358	< 0.01
NDCG@100	0.285	< 0.05
NDCG@10 Gold-Oriented	**0.282**	< 0.05
NDCG@10 Hop-Weighted	0.232	0.057
NDCG@10 First Hop	0.230	0.059
NDCG@10 Best Single Gold	0.166	0.177

Table 16: Spearman correlation between nDCG variants and veracity accuracy by agent type (overall slice). Hop-regularized metrics improve correlation for FIRE and RetrieveFirst but remain weak for DEFAME due to its conservative NEI prediction strategy.

NDCG Metric	FIRE	DEFAME	RetrieveFirst
NDCG@10 / h	0.594**	0.203	0.439*
NDCG@10 / log($h+1$)	0.586**	0.171	0.442*
NDCG@10 / $\sqrt{h}$	0.571**	0.171	0.439*
NDCG@10 Gold-Oriented	**0.460***	**0.096**	**0.439***
NDCG@100	0.436*	0.102	0.454*
NDCG@10 First Hop	0.349	0.105	0.302
NDCG@10 Hop-Weighted	0.277	0.123	0.302
NDCG@10 Best Single Gold	0.249	0.029	0.306

$^{**}p < 0.01$, $^{*}p < 0.05$

claims), while FIRE shows a modest drop (approximately 2%).This relative stability may reflect improved robustness in query generation or suggest that retrieval quality is less sensitive to contamination effects than veracity prediction. However, the observed drops in veracity accuracy (Macro-F_1) are more substantial across all agents when moving from contaminated to uncontaminated claims, indicating that retrieval stability does not fully protect against contamination effects on the final verdict.

This dissociation between retrieval stability and veracity accuracy reinforces that retrieval quality and veracity prediction are coupled but not perfectly aligned, and that strong retrieval does not guarantee accurate verdicts if the agent's decision strategy is overly conservative or if the model's internal beliefs are biased.

E.6 Discussion

Our ablation study reveals that the choice of nDCG aggregation strategy substantially affects the conclusions drawn about retrieval quality in multi-hop agentic fact-checking systems.

Gold-Oriented Aggregation Favors Multi-Attempt Agents. The gold-document-oriented nDCG@10, which takes the best rank for each gold document across all iterations, favors agents that perform more retrieval steps. While this reflects the agent's *eventual* ability to retrieve relevant evidence, it obscures the *efficiency* of retrieval: DEFAME requires approximately four times more iterations than FIRE to achieve similar or only moderately better coverage of gold documents.

Hop-Regularized Metrics Correlate Better with Veracity. Metrics that account for the number of retrieval attempts correlate substantially more strongly with veracity prediction, suggesting that retrieval efficiency, not just final coverage, is predictive of downstream task performance. This makes intuitive sense: agents that retrieve relevant evidence quickly are more likely to integrate it effectively into their reasoning, while agents that require many refinement iterations may struggle with information overload or incoherent evidence accumulation.

Not All Gold Documents Are Equally Important. The weak correlation of nDCG@10 Best Single Gold with veracity suggests that while one highly informative document may be sufficient for prediction, the *method* by which it is retrieved, including the number and quality of alternative documents considered, remains informative about overall system quality. This reinforces that retrieval should be evaluated as a *process* rather than solely by its best outcome.

Recommendation for Future Work. We recommend that evaluations of multi-hop agentic fact-checking systems report both gold-oriented nDCG (as an upper bound on retrieval capability) and a

Table 17: Mean nDCG scores by agent type across all variants (overall slice, all datasets). DEFAME outperforms FIRE on the gold-oriented metric but falls behind substantially when accounting for the number of retrieval iterations. Values shown as percentages.

NDCG Metric	FIRE	DEFAME	RetrieveFirst
NDCG@10 Gold-Oriented	**36.8**	**38.6**	**33.9**
NDCG@10 Best Single Gold	46.4	46.9	45.0
NDCG@10 First Hop	40.6	35.5	40.9
NDCG@10 / $\sqrt{h}$	33.0	19.5	33.9
NDCG@10 / h	30.4	10.6	33.9
NDCG@10 / log(h+1)	45.9	24.8	48.0
NDCG@10 Hop-Weighted	42.9	38.0	40.9
NDCG@5	34.7	36.7	31.8
NDCG@100	40.7	42.7	37.7
Mean Hops	*1.2*	*4.8*	*1.0*

hop-regularized variant such as nDCG/log(h+1) (as a measure of retrieval efficiency). Together, these metrics provide a more complete picture of retrieval quality, distinguishing between agents that retrieve evidence effectively from those that rely on brute-force iteration.

F Hyperparameters

We use consistent hyperparameters across all experiments to ensure fair comparison between retrieval methods and agentic systems. Following the configurations used in DEFAME (Braun et al., 2025) and FIRE (**?**), we set the LLM temperature to 0.0 to ensure deterministic and reproducible results, and top-p to 0.9. While the original DEFAME and FIRE papers used higher top-p values (around 0.9) to encourage diversity in query generation, we opt for deterministic inference to better isolate the effects of retrieval methods and agent architectures without the confounding factor of stochastic query variation.

For retrieval, we use **top-**k=5 documents across all experiments. This value was selected based on an initial hyperparameter search on AveriTeC, which showed that k=5 provided the best trade-off between evidence coverage and information overload. Table 18 shows performance across different k values on a subset of Ex-FEVER using FIRE + GritLM. While k=1 and k=3 showed slightly higher Macro F1 scores, we selected k=5 for consistency with AveriTeC and to ensure sufficient evidence coverage across diverse claim types.

Note that for Ex-FEVER experiments reported in the main paper tables (500 claims), we used k=1 to reduce computational costs, while for the initial 100-claim experiments, we used k=5 (as shown in Table 20 in Appendix **??**).

Top-k	Macro F1
1	64.13
2	56.08
3	64.48
4	50.44
5	57.00

Table 18: Overall performance on the first 100 Ex-FEVER samples using FIRE + GritLM, reported as Macro F1 for different Top-k settings.

All dense retrieval methods use FAISS (Johnson et al., 2021) with `IndexFlatIP` (exact inner product search) to ensure precise ranking without approximation artifacts. For ColBERTv2, we use the standard late-interaction indexing approach provided by the official implementation.

G Label Prediction Analysis by Agent

Figure 3, Figure 4, and Figure 5 show confusion matrices for DEFAME, FIRE, and RETRIEVEFIRST, aggregated across datasets, contamination splits, and retrievers. The matrices reveal systematic differences in prediction behavior. DEFAME exhibits a conservative strategy, frequently predicting NOT ENOUGH INFO, but achieving comparatively higher correctness when predicting SUPPORTED or REFUTED. In contrast, FIRE produces more decisive predictions with higher coverage of non-NEI labels, but also incurs more incorrect assignments.

H Overall Results Including Contamination

For completeness and transparency, we report results aggregated across *all* contamination categories in Table 21 (SciFact), Table 20 (Ex-FEVER,

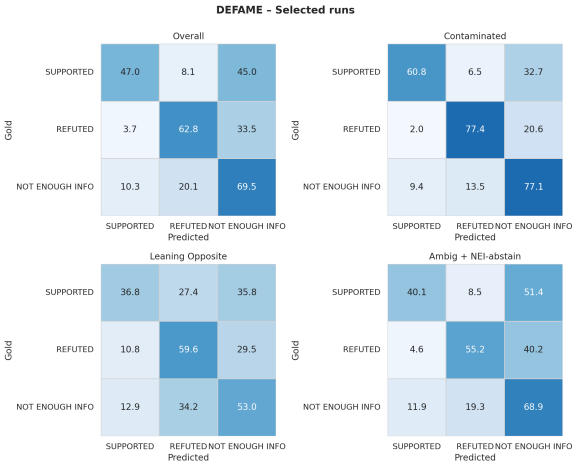

Figure 3: Confusion Matrix of DEFAME across all datasets, splits and retrievers

Figure 4: Confusion Matrix of FIRE across all datasets, splits and retrievers

first 100 samples, Top-k=5), and Table 19 (Ex-FEVER, 500 claims, Top-k=1). These tables include all claims without contamination-bias-based filtering and are provided as a reference complement to the contamination-aware analyses in the main body.

I Ablation AveriTec

J NDCG@Gold Ablations

K Prompt Templates

L Use of AI Assistance

AI-assisted tools were used to support the preparation of this work. Grammarly and ChatGPT helped with grammar, conciseness, and clarity edits, while GitHub Copilot and claude code supported implementation through code suggestions, refactoring,

Figure 5: Confusion Matrix of RetrieveFirst across all datasets, splits and retrievers

and documentation help. The authors reviewed and approved all resulting text and code.

Table 19: EX-Fever retrieval benchmark (Overall claims) Topk=1

Retriever	DEFAME		FIRE		RetrieveFirst	
	Macro-F1	NDCG@10	Macro-F1	NDCG@10	Macro-F1	NDCG@10
Bm25	51.12	53.28	61.31	39.69	40.97	55.36
Contriever	32.52	16.36	52.86	10.86	31.31	16.94
GritHopper	–	–	67.28	90.85	50.40	82.33
GritLM	58.07	78.32	62.67	63.41	50.29	67.23
SBERT	44.86	42.46	50.37	31.17	41.49	35.17
SPLADE	56.68	77.59	62.89	59.74	54.25	60.49

Table 20: EX-Fever first 100 samples with Topk=5 retrieval benchmark (Overall claims)

Retriever	DEFAME		FIRE		RetrieveFirst	
	Macro-F1	NDCG@10	Macro-F1	NDCG@10	Macro-F1	NDCG@10
BM25	–	–	53.21	34.55	48.65	52.74
Contriever	–	–	54.11	11.34	42.57	17.29
GritHopper	–	–	67.22	87.56	57.79	0.00
Gritlm	62.68	81.37	64.74	65.06	54.49	70.51
SBERT	47.19	37.01	54.23	32.01	42.15	33.85
SPLADe	53.47	74.35	57.88	59.37	57.84	61.39

Table 21: SciFact retrieval benchmark (Overall claims)

Retriever	DEFAME		FIRE		RetrieveFirst	
	Macro-F1	NDCG@10	Macro-F1	NDCG@10	Macro-F1	NDCG@10
bm25	61.92	50.01	69.35	40.04	67.99	39.61
colbertv2	56.45	39.86	71.64	35.67	67.97	36.78
contriever	62.87	23.12	66.81	14.22	56.00	19.60
gritlm	63.46	57.43	70.80	51.98	74.53	52.62
SBERT	62.66	39.74	73.56	32.59	70.47	32.95
splade	57.45	53.51	72.63	44.82	73.63	43.35

Prompt A.1: Retrieve-First Veracity Prediction

```
You are a fact-checking assistant. Based solely on the provided evidence, determine
whether the claim is SUPPORTED, REFUTED, or NOT ENOUGH INFO.

Claim: {claim_text}

Evidences:
Evidence 1: {evidence_1}
Evidence 2: {evidence_2}
...

Instructions:
- SUPPORTED: One or more evidences clearly support the claim
- REFUTED: One or more evidences clearly contradicts the claim
- NOT ENOUGH INFO: Considering all evidences, there is not enough information
to determine the claim's veracity

Provide your reasoning and then conclude with exactly one of:
SUPPORTED, REFUTED, or NOT ENOUGH INFO.
```

Figure 6: Retrieve-first prompt template used for veracity prediction.

Prompt A.2: Contamination Tri-Label Probe

```
You are a fact-checking AI. Analyze the following claim and provide your verdict.

Claim: {claim_text}

Respond with ONLY one of these verdicts:
- SUPPORTS: if the claim is factually correct
- REFUTES: if the claim is factually incorrect
- NOT ENOUGH INFO: if there is insufficient information to verify the claim

Verdict:
```

Figure 7: Tri-label contamination probe prompt template.

Prompt A.3: GritLM Query Instructions

Default instruction (claim-based retrieval):

`Given a claim, retrieve documents that support or refute the claim`

Custom instruction (web-search query retrieval):

`Given a web search query, retrieve relevant passages that answer the query`

Figure 8: GritLM query instructions used in our experiments. The custom instruction corresponds to runs tagged with `customInstruction` in the benchmarking scripts.

Table 22: AveriTeC Silver data relevance analysis. Gold NDCG@10 uses only annotated evidence; Combined treats same-claim silver data as additional positives.

Metric	**Value**
Gold NDCG@10	6.4%
Combined NDCG@10	57.5%

Table 23: NDCG@10 Variants by Agent Type (averaged across all datasets)

NDCG Metric	**FIRE**	**DEFAME**	**RetrieveFirst**
NDCG10 (Original)	36.78	38.62	33.89
NDCG10 Best Single Gold	46.41	46.85	44.96
NDCG10 First Hop	40.56	35.48	40.86
NDCG10 / $\sqrt{}$hops	32.96	19.54	33.89
NDCG10 / hops	30.43	10.61	33.89
NDCG10 / log(hops+1)	45.90	24.81	48.04
NDCG10 Hop-Weighted	42.90	37.96	40.86
NDCG5	34.70	36.73	31.76
NDCG100	40.65	42.70	37.66