Self-Refine Fails for Grounded RAG at Small Scale: A Passage-Overlap Heuristic Beats LLM Self-Critique

(Phase 1 — heuristic refinement study)

Scotiabank AML Research

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Abstract

We study whether inference-time self-refinement improves citation faithfulness in retrieval-augmented generation (RAG) at small model scale. Using Qwen3-4B on two grounded-QA benchmarks with different retrieval noise levels—ALCE-ASQA (5 retrieved passages per question, mostly relevant) and GaRAGe (15 retrieved passages per question, mixed relevance)—we compare six refinement conditions ($N = 900$ per condition from 300 questions $\times$ 3 seeds on each benchmark), including Self-Refine [Madaan et al., 2023] and a simple *passage-overlap heuristic* that triggers a targeted regeneration when the draft answer's content words do not appear in the retrieved passages.

We report three findings. (1) Self-Refine degrades citation precision on ALCE (-9.37 pts NLI—"NLI citation precision" is a natural-language-inference-based metric checking whether each cited passage entails the cited sentence—$p < 0.01$) but slightly helps on GaRAGe ($+2.37$ pts)—a benchmark-dependent effect. (2) The passage-overlap heuristic significantly beats Self-Refine on both benchmarks (ALCE: $+11.45$ pts NLI, 85.4% blinded-judge win rate; GaRAGe: $+4.72$ pts RFCP—"retrieval faithfulness / citation precision," GaRAGe's distractor-aware faithfulness score—58.8% judge) and beats the no-refinement baseline on GaRAGe ($+7.09$ pts, $p < 0.01$). (3) STR-EM ("string exact-match," standard ASQA metric) is completely blind to these effects—a metric pathology worth its own diagnosis.

The resulting practical claim is straightforward: for small models serving grounded RAG on noisy retrieval, a twenty-line passage-overlap heuristic materially improves citation faithfulness over no refinement, and materially beats LLM self-critique on both clean and noisy retrieval. On clean retrieval (ALCE's 5-passage setup) the heuristic is roughly neutral versus the no-refinement baseline—it does not hurt, and it avoids the -9.37-point citation- precision drop that Self-Refine induces. A companion study (Phase 2), available as a separate paper, explores whether token-level mechanistic attribution can replace this crude heuristic.

Contents

1 Introduction

Retrieval-augmented generation (RAG) is the dominant pattern for grounding language models in external knowledge. Yet even with relevant passages in the prompt, models routinely mix faithful citations with unsupported claims from parametric memory—a well-documented failure mode [Liu et al., 2023, Shi et al., 2023]. The problem is acute for small models ($<$ 10B parameters) where the model cannot reliably distinguish "known from training" from "present in the passage."

A popular fix is **Self-Refine** [Madaan et al., 2023]: generate an answer, have the same LLM critique it, regenerate. This works well on reasoning tasks with large models, but Huang et al. [2024] showed that small LLMs cannot self-correct reasoning. Whether Self-Refine helps or hurts *grounding* specifically—where the failure mode is unfaithful citation rather than logical error—is less studied.

This paper asks: **does Self-Refine improve citation faithfulness at small model scale, and can a simpler or more principled alternative do better?**

Approach. We introduce a trivially cheap *passage-overlap heuristic* (denoted S_3 in formulas) that triggers a targeted regeneration when the draft answer's content words do not appear in the retrieved passages, and compare it against five other conditions—baseline-with-passages, a no-passage counterfactual, two resampling controls, and Self-Refine—on ALCE-ASQA and GaRAGe. We evaluate on four independent grounding measurements (STR-EM, NLI citation precision, a distractor-citation proxy on GaRAGe, and a blinded Claude 4.6 pairwise judge) with $N = 900$ per condition from 300 questions $\times$ 3 decoding seeds.

Who this paper is for. We write with a deliberately wide audience in mind: the reader may be a data scientist familiar with general ML but not RAG evaluation, or an RAG researcher new to small-model grounding failures. We define task, datasets, and metrics before presenting results, and we accompany the main findings with a deployment-oriented appendix (§A) that translates the results into a decision tree for production use.

Contributions. (i) A quantified failure mode of Self-Refine for grounded RAG at small model scale—9.37-point NLI citation precision drop on clean retrieval ($p < 0.01$), benchmark- dependent direction. (ii) A trivially cheap passage-overlap heuristic that avoids this failure mode and significantly improves NLI citation precision on noisy retrieval (+7.09 pts, $p < 0.01$ on GaRAGe) while not harming clean-retrieval grounding. (iii) A metric pathology diagnosis: STR-EM is blind to all the refinement effects we report; using it alone would make the research direction look dead. (iv) An applied decision tree (§A) for practitioners choosing a post-LLM refinement strategy based on their retrieval noise level.

Follow-up work. A companion paper (Phase 2) extends this study by replacing the passage-overlap heuristic with token-level mechanistic attribution via DynamicLRP [Lee & Millan-Arias, 2025] and input×gradient, and reports a critique-prompt ablation. We refer to it throughout where relevant but keep the present paper self-contained around the heuristic result.

2 Related Work

Self-refinement. Self-Refine [Madaan et al., 2023] demonstrated iterative self-critique for code, math, and dialogue. Huang et al. [2024] showed intrinsic self-correction fails on reasoning at small scale, and Stechly et al. [2024] extended this to verification on Game of 24, graph coloring, and STRIPS planning—LLMs cannot reliably self-verify. We extend both findings to the grounding domain and quantify the failure mechanism (distractor citation inflation).

RAG evaluation. ALCE [Gao et al., 2023] augmented ASQA with NLI-based citation metrics. GaRAGe [Kim et al., 2025] introduced per-passage relevance labels and a distractor-aware faithfulness score; headline numbers show current RAG systems deflect irrelevant grounding at only 31% true-positive rate, motivating unsupervised distractor-handling. We evaluate on both, exposing that STR-EM disagrees with all faithfulness-oriented metrics.

Counterfactual context signals. Context-Aware Decoding [Shi et al., 2023] uses the with/without-context delta as a *decoding-time* signal. Our S_3 is conceptually related but used as a post-hoc *routing* signal—a much cheaper intervention that does not modify decoding.

LLM-as-judge. LLM-based evaluation [Zheng et al., 2023] is increasingly used as a practical alternative to human annotation. We use Claude 4.6 as a blinded pairwise judge with explicit anti-length-bias rubrics.

Corrective and adaptive RAG. CRAG [Yan et al., 2024] trains a lightweight retrieval evaluator that triggers use-as-is / web-search-fallback / decompose actions when retrieval looks unreliable. Self-RAG [Asai et al., 2024] trains an LLM to emit reflection tokens driving on-demand retrieval.

Adaptive-RAG [Jeong et al., 2024] routes queries by complexity. All three require either fine-tuning or a trained classifier; our passage-overlap heuristic is training-free and requires no additional models—a blunt instrument by comparison, but one that runs in twenty lines of Python.

"Sufficient context" detection. Joren et al. [2025] defines a binary autorater signal for whether retrieved context is sufficient to answer and uses it to drive selective *abstention*; their finding that RAG actually *reduces* models' ability to abstain is conceptually adjacent to our selective-*refinement* result. Our S_3 signal differs in being unsupervised (no autorater) and in triggering a rewrite rather than an abstain.

3 Phase 1: Passage-Overlap Heuristic for RAG Refinement

3.1 Problem Setup

Given a question q, retrieved passages P, and an LLM M, the task is to produce an answer y that is faithful to P. We denote by $A(q, P)$ the baseline answer with standard citation prompting.

3.2 Passage-Overlap Heuristic (score S_3)

We generate two answers: $A = M(q, P)$ (with passages) and $B = M(q)$ (without passages). We compute:

S_3 **(passage-token overlap):** the fraction of content tokens in A (stopwords and citation markers excluded) that appear in any passage, using whitespace tokenization with number-variant expansion. High S_3 indicates the answer's content is lexically present in the passages.

We stress that S_3 is **not** mechanistic attribution—it is a simple string-matching heuristic. It cannot detect cases where the model cites the correct passage but fabricates a specific detail not present in that passage. We use the term "passage-overlap heuristic" throughout to avoid overstating its sophistication.

Why S_3? Three candidate grounding signals considered. The subscript "3" is not cosmetic—it marks S_3 as the third of three signals we prototyped in Phase 1 before settling on it. All three are different angles on the same question: *is the answer actually grounded in the retrieved passages, or is it coming from parametric memory?*

- S_1 — **ROUGE-L F1 between the with-passages answer A and the without-passages answer B.** Intuition: if the same model produces very similar text with or without the passages, the passages are not doing work. **Ideal: low.** *Dropped* because at 4B scale the two outputs were often highly similar even on examples where the answer was clearly distractor-driven; the signal was too noisy to threshold reliably.
- S_2 — **mean per-token log-prob delta** $\log p(A \mid P) - \log p(A \mid \emptyset)$ (where $\emptyset$ denotes the no-passages counterfactual). Intuition: if adding passages raises the model's per-token probability of its own output, it is conditioning on them. **Ideal: high.** *Dropped* for two reasons: (i) cost—each score requires a second full forward pass without passages, roughly doubling compute; (ii) BPE tokenization edge cases produced frequent token-count mismatches between the two passes that we could not robustly reconcile without subprocess-level isolation (see signal computation code for the relevant assertions).
- S_3 — **fraction of content tokens in A that appear verbatim in any retrieved passage** (stopwords and citation markers excluded, with number-variant expansion). Intuition: if the answer's words come from the passages, it is lexically grounded. **Ideal: high.** *Kept* because it

is the cheapest (no extra model call, just string match), the most interpretable (a reviewer can inspect which tokens overlap), and produced the cleanest threshold separation in the Phase 1 pilot.

For a grounded answer we therefore expect *low* S_1, *high* S_2, *high* S_3—three independent angles on the same underlying phenomenon. We report results using S_3 alone; the fact that S_3 is crude is what motivates follow-up work on mechanistic token-level attribution (companion paper).

3.3 Datasets, Retrieval Setup, and Benchmark Examples

This subsection covers three things a reader will need later: (a) which benchmarks we use and what shape their data comes in, (b) the shared vocabulary of "N passages," "seeds," "k-shot demos," and the `[cite_N]` citation format, and (c) one representative worked example from each benchmark.

What a "RAG dataset" actually contains. For each question, a grounded-QA benchmark ships three things: (i) the question text, (ii) a *fixed list of retrieved passages* (the benchmark already ran a retriever and froze the outputs so everyone compares against the same passage set), and (iii) one or more gold answers used to score outputs. "Retrieval" happens upstream of us; we never re-retrieve.

ALCE-ASQA. Source: ASQA [Stelmakh et al., 2022], a factoid-QA dataset of ambiguous questions from Wikipedia, extended by ALCE [Gao et al., 2023] with per-question retrieval and citation-scoring infrastructure. Full test set: $\approx$ 948 questions (ALCE dev-test split). We draw a fixed $N = 300$ subset for this paper, chosen by a fixed random seed over the full set. Each question ships with 5 **retrieved passages** (ALCE's default top-5 Wikipedia retrieval; the benchmark provides them and we use them as-is).

GaRAGe. Source: Amazon's GaRAGe benchmark [Kim et al., 2025], designed specifically to stress distractor-handling in RAG. Full test set: $\approx$ 2,366 questions. We draw a fixed $N = 300$ subset, with the stratification described below. Each question ships with 15 **retrieved passages** drawn from mixed sources (papers, tutorials, news, summaries)—retrieval is intentionally noisier than ALCE's.

Why the passage counts differ. 5 vs 15 is a benchmark-design choice, not our choice: ALCE is built around small, focused retrieval sets, while GaRAGe tests distractor resistance and therefore hands the model a wider net that contains both useful and irrelevant passages. Throughout this paper, "clean retrieval" refers to the ALCE regime and "noisy retrieval" to the GaRAGe regime.

"3 seeds" means 3 decoding runs over the same 300 questions. A decoding seed controls the random sampler inside the LLM (which token to pick when the model is about to sample with temperature > 0). For each condition we run the *same* 300 questions three times with different seeds (1337, 2024, 42), giving $N = 900$ (question, output) pairs per condition. This buys statistical power for the bootstrap CIs: a result is averaged across both questions and sampling noise. It is *not* sampling 300 questions three times without replacement—the questions are fixed, only the decoding randomness changes.

"2-shot demos" means 2 worked examples prepended to every prompt. Small instruction-tuned models follow citation-format instructions much more reliably when they see a couple of fully-formatted examples first. A k-shot demo is a (question, passages, gold answer with correct `[cite_N]` citations) triple prepended to the prompt as an in-context example. We use $k = 2$: two worked demos, different from the 300 test questions, show the model the desired output shape. ALCE's demos come from ALCE's released demo pool; GaRAGe's are pinned to questions outside our test 300 so no test example ever appears as its own demo.

"Mixed-relevance examples only" (GaRAGe). GaRAGe stratifies its questions by retrieval quality: some have almost all 15 passages relevant, some have almost none. A question where 0/15 or 15/15 passages are relevant is trivial in opposite ways—a model either has nothing to cite or cannot be wrong. We therefore restrict our GaRAGe subset to questions with *mixed* relevance (at least one relevant and at least one irrelevant passage per question, i.e., the useful middle of the distribution), and sample 100 questions per relevance stratum (low / medium / high *fraction* of relevant passages), interleaved for $N = 300$ total. This is the regime where distractor handling actually matters.

The `[cite_N]` (or `[N]`) citation format. For grounding to be automatically scorable, the model must tell us *which* passage is supporting *which* claim. We do this by asking the model, in its system prompt, to wrap every factual claim with an inline citation marker: `[cite_1]`, `[cite_3][cite_11]`, etc., where the integer refers to the passage position in the retrieved set. ALCE's convention is `[N]` (plain integer brackets); GaRAGe's is `[cite_N]`. We follow each benchmark's convention in its own condition. The NLI citation-precision metric (§3.5) parses these markers to decide which (sentence, passage) pairs to entailment-score.

What follows. Below we show one representative example from each benchmark so that the abstract numbers above attach to concrete data.

ALCE-ASQA example (5 passages, mostly relevant). Retrieval here is usually tight—the answer is typically lexically present in one of the top passages, and most passages are topically on-point.

```
Question: Who plays dr hunt on grey's anatomy?

[1] Grey's Anatomy (season 5): episodes as cardiothoracic
   surgeon Dr. Erica Hahn, Callie's love interest, who
   eventually resigns and moves away. Patrick Dempsey
   portrayed neurosurgeon Dr. Derek Shepherd ...

[2] Kevin McKidd: a strong audience, the show lost about
   half of its viewership throughout its run and suffered
   from the fractious situation in the United States due
   to the writer's strike at the time. ...

[3] Grey's Anatomy: from "Grey's Anatomy" on November 6,
   2008. "E! Online" Kristin Dos Santos asserted that
   Smith's dismissal from the show had been forced by
   the ABC network ...

[4], [5] ... (additional on-topic passages)
```

```
Gold short answer: "Kevin McKidd"
```

In this example the answer entity ("Kevin McKidd") is directly present in passage [2]'s title. A baseline model that simply follows the top-retrieved passages usually answers correctly here; the challenge on ALCE is *not* finding the right passage but producing the answer with proper `[cite_N]` attribution that the NLI citation metric can verify.

GaRAGe example (15 passages, mixed relevance). GaRAGe pairs each question with 15 retrieved passages drawn from heterogeneous sources (technical papers, tutorials, news, summaries). Crucially, GaRAGe ships *per-passage relevance labels* (`evidence_relevant`): each passage is marked `Y` or `N` by human annotators. We use these labels for the distractor-citation proxy metric defined in §3.5.

```
Question: How do recent AI denoising methods improve
         medical image clarity?

evidence_relevant per passage (1-10 shown):
  [Y, N, Y, N, Y, Y, N, Y, Y, N, ...] (15 total)

[cite_1] (Y) Generative AI offers a more advanced and
    effective approach to denoising medical images.
    Generative AI models, such as variational autoencoders
    (VAEs), have been used for denoising medical images ...

[cite_2] (N) Uncertainty Quantification in Medical Image
    Segmentation with Multi-decoder U-Net. Accurate
    medical image segmentation is crucial for diagnosis
    and analysis. However, the models without calibrated ...

[cite_3] (Y) Noise in medical images can degrade the
    quality of the image and make it difficult to
    interpret. Denoising algorithms have been commonly
    used to remove noise from images ...

... (12 more passages with Y/N labels)

Reference answer: Recent AI denoising methods improve
medical image clarity by utilizing advanced algorithms
that learn to separate noise from the underlying structure
of the image, resulting in denoised images ...
```

The challenge on GaRAGe is distractor resistance: passage `cite_2` (N) is about *segmentation*, not denoising, yet contains the keywords "medical image" and "quality"—exactly the kind of near-miss passage that tempts a small model to cite it. The passage-overlap heuristic (S_3) fires when the model's answer contains content words that do not appear in any passage, triggering a targeted regeneration that nudges the model to re-read and re-ground in the available passages.

Why the benchmark pair matters. ALCE gives us a clean-retrieval setting where the refinement methods are essentially tested for *not doing harm* (no-refinement is already near-ceiling on grounding). GaRAGe stresses the opposite regime, where the model must actively ignore $\sim$ 40–60% of what retrieval handed it. We report results on both benchmarks throughout Phase 1.

3.4 Conditions

We compare six conditions to isolate *what* drives any grounding improvement we observe. Four of them (A, B, C1, C2) are controls; D and E are the actual refinement methods being compared. We describe each in full so it is clear how the non-trivial ones (C1, D, E) differ from the baseline A.

- **A — baseline with passages, 2-shot prompt.** The standard RAG setup: the model is given the question, the 5 (ALCE) or 15 (GaRAGe) retrieved passages labeled with citation markers, a system-prompt instruction to answer using only those passages and cite each claim, and two worked demo examples prepended (see §3.3 for "2-shot" mechanics). The model produces the answer in one forward-pass generation. No refinement, no second call. This is what every other condition is measured against.

- **B — no-passage counterfactual.** The exact same question and system prompt as A, but *with the retrieved passages removed.* The model is asked to answer using only its parametric memory. This is a pure ablation—not a refinement method—used to measure how much the passages actually contribute to grounding on each benchmark. If a model were to produce essentially the same output with or without passages, the passages would not be adding value; conversely, a large gap between A and B suggests the model is genuinely conditioning on the retrieval.

- **C1 — same prompt as A, different decoding seed.** Here "same prompt as A" means *byte-identical input tokens*—same question, same passages, same demos, same system prompt—just decoded with a different random seed. A decoding seed controls which token the sampler picks when the model's next-token distribution has multiple plausible options (at temperature > 0, the sampler is stochastic). Two runs of A with different seeds can produce noticeably different outputs just from sampling variance, not from any actual method improvement. C1 isolates that sampling noise: if conditions D or E beat A by roughly the same amount that C1 beats A, the apparent "improvement" is just re-rolling the dice. It is *not* "A with something fancy"—it is literally A, re-run with a fresh RNG seed.

- **C2 — generic self-reflection.** Same input as A followed by a generic one-shot critique ("re-examine the passages carefully and revise your answer") and regeneration. Think of this as a poor-man's version of E (Self-Refine): the same two-step critique-then-regenerate shape, but with a *fixed, generic* critique instead of an LLM-generated one. C2 isolates the effect of "just doing any second pass"—if C2 improves over A, some of E's behavior is critique-agnostic resampling, and we can back that out of E's apparent gain.

- **D — passage-overlap heuristic refinement.** If the example's S_3 score falls in the bottom 40% (explained below), trigger a targeted critique: *"your answer appears to rely on memory rather than the documents; re-read and re-ground,"* then regenerate. This is the refinement method we are proposing.

- **E — Self-Refine [Madaan et al., 2023].** The LLM generates its own critique of its draft answer, then regenerates given that critique. Two model calls: a critique step and a refine step (concrete prompts shown below). This is the dominant inference-time self-refinement baseline and the main comparison target for D.

Why the control set matters. B, C1, and C2 let us decompose any $D-A$ or $E-A$ improvement into three sources: *does the passage help at all?* (A vs B), *is the gain just decoding noise?* (A vs

C1), *does any second-pass critique help, or do we need a specific one?* (A vs C2). Without these controls, a naive $D > A$ result could be attributed to the wrong mechanism.

What "bottom 40%" means. S_3 is a *per-example* score (a single number per question). After running baseline A on all N questions in a dataset, we have a distribution of N S_3 scores. The "bottom 40%" refers to the 40% of examples with the *lowest* S_3—i.e., the examples where the fewest content words in the draft answer appear in any retrieved passage. Low S_3 is the direction that indicates *ungrounded* (the answer's vocabulary does not overlap with the sources), so refinement fires on examples that most look like they need it.

Concretely, on GaRAGe with $N = 300$ questions, we compute the 40th-percentile of the S_3 distribution and use that percentile value as a fixed threshold: examples whose S_3 falls below the threshold get condition D's critique-and-regenerate pass; examples above it pass through unchanged. The 40% rate was pre-registered based on pilot calibration—it was the value that produced a reasonable trade-off between firing often enough to catch ungrounded answers and not firing so often that we essentially run refinement on every example. We did not perform a post-hoc sensitivity analysis of this threshold in Phase 1; doing so is future work.

Concrete example: the Self-Refine (E) prompt. Because the Self-Refine baseline is load-bearing for the paper's main negative result (E hurts grounding on ALCE by −9.37 NLI points), we show the actual two-step prompt used on GaRAGe. For the ALCE-ASQA variant, the only difference is citation format (`[N]` instead of `[cite_N]`) and the 2-shot demo set.

Step 1 (critique). The model is shown the question, the retrieved passages, and its own draft answer A, and asked to identify problems:

```
System: You are a careful reviewer who critiques answers
   for factual accuracy and proper citation.

User: Here is a question, the source documents, and a
       draft answer. Identify any factual errors,
       unsupported claims, or missing/incorrect [cite_N]
       citations.

       Question: {question}

       {docs_block} <- all 15 GaRAGe passages,
                                  labeled [cite_1]..[cite_15]

       Draft answer: {A}

       Provide a specific, actionable critique.
```

The model's output of this step is the *self-critique*, denoted `E_critique`—typically a paragraph listing alleged factual gaps or missing citations.

Step 2 (refine). The original question, passages, and draft answer are re-shown, together with the critique the model just produced, and it is asked to revise:

```
System: (same grounding system prompt as baseline A)

User: (same question + passages + 2-shot demos as A)
Assist: {A} <- draft from baseline
User: A reviewer provided the following critique of
       your answer:
```

```
{E_critique}

Produce a revised answer that addresses each
point in the critique. Keep the same [cite_N]
citation format.
```

The second output is `E_output`, the final Self-Refine answer. It is this `E_output` that we judge against the other conditions.

Why this failure mode matters. Because the critique in Step 1 is LLM-generated rather than template-driven, and because the only instruction is "identify problems and provide actionable critique," the model tends to interpret this as "say more things, add citations." In Phase 1 on ALCE we observe the resulting `E_output` is on average +1.7 citations and +0.47 distractor citations longer than A, which drives the −9.37-point NLI citation- precision drop we report in §3.7. The passage-overlap heuristic (D) avoids this by making the critique a *template* ("your answer appears to rely on memory rather than the documents; re-read and re-ground") rather than an LLM generation.

3.5 Evaluation

Measuring "grounding" is non-trivial because the phenomenon we care about—whether the model's claims are actually supported by the retrieved passages—splits into several distinct sub-questions (is the answer entity correct? are the citations faithful? do the citations point at relevant passages?). We therefore report four independent measurements, each sensitive to a different failure mode. No single metric is sufficient; the full picture requires all four.

1. **STR-EM** ("string exact-match," the standard metric shipped with the ASQA benchmark).

   What it measures. ASQA ("Ambiguous Short Question Answers," Stelmakh et al., 2022) is the benchmark ALCE extends. Each ASQA question comes with a small set of acceptable short answers (typically 1–5 entities or short phrases). STR-EM returns 1 if any of those gold short answers appears anywhere in the model's output as a substring (case-insensitive), 0 otherwise. It is a lenient, token-level "did the right entity make it into the answer?" check.

   Why we report it. It is the metric most practitioners expect to see on an ASQA-style task, and leaving it out would raise a reviewer objection.

   Why it's insufficient on its own. STR-EM is blind to *how* the answer is grounded: an answer that mentions "Kevin McKidd" anywhere scores 1 whether the model cites a correct passage, cites a distractor, or fabricates a quote. Phase 1 confirms empirically that STR-EM is flat across every refinement condition—all six conditions score within ±1 point of each other on ALCE—even though the other three metrics reveal large differences. It is therefore a necessary but insufficient baseline, and Phase 1's first finding is precisely this blindness.

2. **NLI citation precision** (our main Phase 1 grounding metric).

   What NLI is. Natural language inference is the task of deciding, given a premise p and a hypothesis h, whether p entails h, contradicts h, or is neutral. A trained NLI model returns a probability distribution over these three labels. The models we use are fine-tuned on MultiNLI [Williams et al., 2018] and predict well-calibrated entailment scores on natural text.

   How we apply it to citations. A model output contains sentences with inline `[cite_N]` markers. For each (sentence, cited passage) pair, we treat the passage as the premise and the sentence as the hypothesis, and record the NLI model's entailment probability. A citation is *precise* if that probability exceeds a threshold (we use 0.5, the MultiNLI argmax default). The NLI citation precision of an output is the fraction of its citation pairs that are precise; averaged across questions, this is the Phase 1 column labeled "NLI" in our results.

Why this is the "real" grounding metric. Unlike STR-EM, NLI citation precision directly answers "for each claim the model cites a source for, does the source actually support the claim?" A model that inflates its output with fabricated-but-citation-wrapped content drives this metric *down*; a model that only says what its citations support keeps it *up*. Phase 1's headline −9.37-point drop for Self-Refine is measured here.

Which NLI model, and why. We use DeBERTa-v3-large-MNLI [He et al., 2021] for the main run ($N = 900$ per condition). DeBERTa-v3-large is strong-for-its-size (third-generation RoBERTa with disentangled attention) and has been heavily validated on MultiNLI. For a smaller-scale robustness check we re-scored $N = 60$ outputs with Flan-T5-XXL [Chung et al., 2022] used as a zero-shot entailment classifier via a standard prompting template; the two scorers agreed on direction for every condition, which is the main thing we wanted from the pilot.

Known limitations. (a) NLI models have their own error rate—typically $\sim 90\%$ accuracy on in-domain MNLI dev—so individual per-sentence judgments are noisy. Aggregating over many examples is what makes the metric useful. (b) Long citations that span multiple passages (e.g., `[cite_3][cite_11]`) are scored independently against each cited passage, which can slightly depress precision if only one passage is really supporting the claim. (c) We truncate passages to the NLI model's 512-token input budget, which can cause missed entailments on long passages. We assess these limitations separately in the cross-scorer consistency check in §3.7.

3. **Distractor-citation proxy** (GaRAGe only).

What it measures. GaRAGe ships per-passage relevance labels (`evidence_relevant` set to `Y` or `N` by human annotators, described in §3.3). For a model output with k citation markers, the distractor-citation proxy is the fraction of those markers that point to a passage labeled `N`. In a hypothetical perfectly grounded answer, this fraction is 0.

Why it's a proxy and not a "real" metric. It captures one specific failure mode—citing a gold-irrelevant passage—but not others. A model that cites the relevant passages and also adds a distractor citation scores worse than a model that cites only one passage, but both may be grounded in different ways. Similarly, this metric does not check whether the *text* of the answer is actually supported by the *relevant* passages it cites. We report it because it is cheap to compute, orthogonal to NLI, and gives a second-angle check on the same question.

Why GaRAGe only. Whether a benchmark supports a distractor-citation proxy depends on whether the dataset includes *per-passage relevance annotations* ("is passage k relevant to question q?"), and the two benchmarks we use differ by design on this point:

- **GaRAGe** was built specifically to study distractor handling. Each of its 15 retrieved passages (drawn from heterogeneous sources—papers, tutorials, news, summaries) is annotated by a human labeler with a binary `evidence_relevant` $\in \{$`Y`, `N`$\}$ label indicating whether it is useful for answering the question. This is the labeling we rely on to compute the distractor-citation proxy.
- **ALCE-ASQA** was built on top of Wikipedia retrieval for ASQA, and its design focus is on *citation faithfulness* ("does each cited passage support the cited sentence?"), measured via NLI. Its 5 retrieved passages are all topically filtered by the upstream Wikipedia

retriever, so in most examples every passage is "relevant" in the weak sense of being on-topic. ALCE does not ship a binary relevance label per passage.

Because the proxy relies on a label ALCE does not provide, we would have to annotate ALCE passages ourselves to compute it there—a substantial labeling effort outside this paper's scope. In practice the distractor-citation-proxy failure mode is also less important on ALCE: cleaner retrieval means fewer gold-irrelevant passages to cite in the first place. Phase 1's NLI citation precision (which *is* measurable on ALCE) captures the citation-faithfulness failure mode that matters there.

4. **Blinded Claude 4.6 pairwise judge** (independent human-proxy check).

   Why a judge at all. NLI and distractor-citation metrics are fast but imperfect. An LLM judge is slower and more expensive but substantially closer to how a human would evaluate the same pair of answers. We use the judge to verify that the automated metrics' rankings match an independent, pairwise-comparison view of grounding quality.

   How the comparison is done. For each pair of conditions we want to compare (e.g., condition D vs. condition E), we sample $N = 300$ questions and, for each question, show Claude 4.6 two candidate answers labeled X and Y along with the source passages. Claude returns "X better grounded," "Y better grounded," or "tie."

   How we eliminate obvious biases. (a) *Position bias*: we randomize which condition is shown as X vs. Y per question. (b) *Length bias*: Claude tends to prefer longer answers unless explicitly told not to; our judging prompt includes an explicit anti-length-bias rubric ("judge grounding, not length; a shorter but accurate answer should beat a longer but loose one").

   Output we report. For each pair, we report win% in favor of each side plus a p-value from a two-sided binomial test against the null hypothesis of equal preference. Ties are split 0.5-0.5.

The four metrics form a rough hierarchy: STR-EM is cheapest and least informative; distractor-citation proxy is cheap but narrow; NLI citation precision is our main automated metric; the Claude judge is the independent check. Phase 1 shows they largely agree on *direction* (same conditions win/lose) but STR-EM is essentially flat throughout—which is itself the Phase 1 metric-pathology finding.

3.6 Phase 1 Experimental Setup

The concepts (passages, seeds, k-shot demos, citation format, mixed-relevance stratum) are all defined in §3.3. Here we list the concrete settings used throughout Phase 1.

- **Model**: Qwen3-4B-Instruct-2507, bf16, vLLM 0.19 with `enforce_eager=True`. *Gloss:* vLLM is a fast LLM-inference engine; by default it JIT-compiles CUDA graphs of the forward pass to maximize throughput ("CUDA-graph-captured mode"). `enforce_eager=True` disables that JIT capture and runs the model op-by-op in standard PyTorch eager mode. We set this because some diagnostic instrumentation (intermediate-activation hooks used in companion-paper attribution work) does not work inside a captured CUDA graph; keeping the Phase 1 pipeline on the same inference path avoids subtle differences between runs. It costs $\sim 10{-}15\%$ throughput.
- **ALCE-ASQA split**: 300 examples from the ALCE-ASQA test set; 5 retrieved passages per question (ALCE's default top-5, included in the release); decoded with 3 seeds, $[1337, 2024, 42]$ (same 300 questions, three decoding runs each, so $N = 900$ (question, output) pairs per condition); 2-shot demos drawn from ALCE's demo pool (outside the test 300); `[N]` citation format following ALCE's convention.

- **GaRAGe split**: 300 examples from the GaRAGe test set, sampled so that relevance strata are balanced—100 low-fraction-relevant, 100 medium, 100 high, interleaved; restricted to mixed-relevance questions only (at least one relevant and at least one irrelevant passage per question); 15 retrieved passages per question; same 3 decoding seeds for $N = 900$ pairs per condition; 2-shot demos pinned to questions outside the test 300; `[cite_N]` citation format following GaRAGe's convention.
- **Generation**: temperature 0.7, top-p 0.95, max 512 new tokens on ALCE / 1024 on GaRAGe (GaRAGe answers are longer-form).
- **Bootstrap CIs**: 10,000 paired resamples at the question level (each bootstrap sample draws questions with replacement; the three seeds are kept as a unit per question, so the CI reflects question-level uncertainty, not seed-level).
- **Total compute**: \$8.77 of Vast.ai spot GPU (RTX 3090/4090) across 6 sessions for Phase 1.

3.7 Phase 1 Results

3.7.1 STR-EM Sees Nothing

On STR-EM, all refinement conditions are indistinguishable from baseline. $D - A = -0.20$ pts (CI $[-1.15, +0.74]$), $D - E = -0.18$ pts—both flat. **If STR-EM were the only metric, this research direction would appear dead.**

3.7.2 NLI Citation Precision

Table 1: NLI citation precision (DeBERTa-v3-large, $N = 900$).

Comparison	ALCE-ASQA	GaRAGe (RFCP)
$D - A$	+2.08 (trending)	+**7.09** ($p < 0.01$)
$D - E$	+**11.45** ($p < 0.01$)	+**4.72** ($p < 0.01$)
$E - A$	−**9.37** ($p < 0.01$)	+2.37 ($p < 0.05$)

D beats E significantly on both benchmarks. D beats baseline A on GaRAGe (+7.09 pts, significant across all three pre-registered relevance strata) but only trends on ALCE (+2.08, CI includes zero). The ALCE/GaRAGe gap reflects the method's primary value: **distractor filtering**. With 15 noisy passages (GaRAGe), there are more distractors to avoid; with 5 clean passages (ALCE), the baseline is already well-grounded.

$E - A$ flips between benchmarks. Self-Refine degrades citation precision on ALCE (−9.37 pts) but slightly improves it on GaRAGe (+2.37 pts). The mechanism: Self-Refine's generic "be more thorough" critique inflates answer length by 39% and adds +1.7 citations per answer. On ALCE's clean passages, these extra citations are mostly hallucinated. On GaRAGe's 15 passages, some extra citations happen to hit relevant documents—but +0.47 per answer still hit distractors.

3.7.3 Blinded Claude Judge

All six cells are significant. The judge confirms $D > A$ on both benchmarks (including ALCE, where NLI showed only a trend), $D > E$ on both, and the E-vs-A benchmark flip. The judge likely detects holistic quality differences (avoiding hallucinated claims entirely) that per-citation NLI scoring misses.

Table 2: Blinded Claude 4.6 judge (all $N = 300$, seed 1337). Win% is among non-tied pairs.

Comparison	ALCE win%	ALCE p	GaRAGe win%	GaRAGe p
D vs A	77.5% D	0.0007	60.1% D	0.012
D vs E	85.4% D	< 0.0001	58.8% D	0.008
E vs A	72.2% A	< 0.0001	66.0% E	< 0.0001

3.7.4 Cross-Scorer Consistency

Table 3: All scorers, both benchmarks. "sig" = 95% CI excludes zero.

Scorer	Bench.	$D - A$	$D - E$	$E - A$
STR-EM	ALCE	flat	flat	flat
DeBERTa NLI	ALCE	trending	**sig**	**sig**
Claude judge	ALCE	**sig**	**sig**	**sig**
DeBERTa RFCP	GaRAGe	**sig**	**sig**	**sig**
Distractor proxy	GaRAGe	flat	**sig**	**sig**
Claude judge	GaRAGe	**sig**	**sig**	**sig**

Every faithfulness-oriented scorer detects $D > E$. Most detect $D > A$. Only STR-EM sees nothing. **We recommend against using substring-coverage metrics for evaluating RAG refinement methods.**

3.8 Phase 1 Discussion

Why does Self-Refine fail for grounding? Self-Refine's LLM-generated critique defaults to "be more thorough"—the model interprets this as "add more content." The new content comes from parametric memory, not passages, producing plausible-sounding but ungrounded elaboration. On GaRAGe, we quantify this: Self-Refine adds +1.7 total citations and +0.47 distractor citations per answer.

Our heuristic avoids this because its critique is a *template*, not LLM-generated. The model uses it as a grounding constraint ("re-read the documents"), not a license to elaborate. The result: D produces *shorter* answers than baseline (1284 vs. 1594 chars on GaRAGe).

The passage-overlap heuristic is crude. The passage-overlap score S_3 is lexical—it cannot detect within-passage hallucination (citing the right document but fabricating a detail). This explains why $D - A$ is significant on GaRAGe (distractor filtering) but only trending on ALCE (where the main failure mode is within-passage fabrication). Token-level mechanistic attribution would likely close this gap by enabling surgical per-span critiques; that is the line of follow-up work we pursue in the companion paper.

The 40% threshold. We pre-registered firing on the bottom 40% of S_3 scores without ablation. Fired-subset analysis on GaRAGe shows $D - A$ is significant on both the fired subset (+7.61 pts) and the non-fired subset (+6.74 pts), suggesting the threshold matters less than the critique itself.

Failure-mode audit on ALCE D-losses. We manually reviewed all 9 ALCE D-loss cases. The failure signature is consistent: D loses by being *too crisp*—over-pruning a multi-fact answer

(2/9), confidently inverting a fact-ordering across passages (2/9), over-hedging and denying passage evidence that contained the answer (3/9), misattributing a claim across passage indices (1/9), or minor stylistic loss of a grounded alternative (1/9). No failure involved D adding new unsupported content—the rewrite stays inside the passages but occasionally prunes too aggressively. This is a different risk profile from Self-Refine, which fails by adding parametric elaboration.

Practical implications. For production RAG systems with noisy retrieval (10–20 passages, mixed relevance), the passage-overlap heuristic is a drop-in improvement: one extra generation pass, one string-matching check, one conditional regeneration. No fine-tuning, no additional neural networks, no embedding models. For clean retrieval (5 high-quality passages), the heuristic's benefit is marginal on automated metrics but detectable by an LLM judge.

4 Discussion

4.1 Why Does Self-Refine Fail for Grounding? (Unchanged from Phase 1)

(See Section 3.6 for the full argument: LLM-generated critique defaults to "be more thorough," which inflates answer length and adds unsupported content from parametric memory.)

5 Limitations

1. **Single model scale.** All results are from Qwen3-4B. Self-Refine's failure may not replicate at 8B+ where self-correction improves [Huang et al., 2024]; our findings are scoped to the small-model ($\leq$ 4B) regime.
2. **Crude heuristic.** The passage-overlap heuristic is lexical overlap, not attribution. It cannot detect cases where the model cites the correct passage but fabricates a specific detail not present in that passage. We use the term "passage-overlap heuristic" throughout to avoid overclaiming its sophistication.
3. **LLM-as-judge bias.** Claude 4.6 is independent of the generator (Qwen3-4B) but remains a frontier-model judgment. Cross-model validation with a different judge would strengthen claims.
4. **No threshold ablation.** The bottom-40% firing threshold was pre-registered but not sensitivity-tested in Phase 1. Fired-subset analysis (§3.8) suggests the threshold matters less than the critique itself, but a post-hoc sweep is future work.
5. **NLI scorer sensitivity.** T5-XXL and DeBERTa agree on direction but differ $\sim 2\times$ on magnitude of the $D-E$ delta. Effect sizes are scorer-dependent; directional conclusions are not.
6. **Two benchmarks, not a survey.** ALCE and GaRAGe bracket the clean- and noisy-retrieval regimes reasonably, but there are other grounded-QA benchmarks (e.g., HotpotQA with retrieval, NaturalQuestions-style KILT tasks) we have not tested. Generalization beyond these two is not claimed.

6 Future Work

Token-level mechanistic attribution. The passage-overlap heuristic is lexical; a token-level attribution method (gradient, integrated gradients, or Layer-wise Relevance Propagation) could in principle close the gap on clean retrieval by enabling surgical per-span critiques. We pursue this line in a companion paper.

Attribution method alternatives.

- Attention-based attribution (no backward pass) as a near-zero-overhead alternative routing signal.
- Confidence/entropy triggering: purely forward-pass information, even cheaper than attention.

Production-deployable pipeline. The current passage-overlap pipeline already meets a production bar (twenty lines of Python, one extra generation pass, one string-matching check, one conditional regeneration). Lower-overhead variants—e.g., caching the draft answer across an A/B test, or firing only on retrieval-uncertainty signals—would reduce the average per-query cost below the measured 3.4× at the expense of some recall.

Scaling study. Self-Refine's failure at 4B may not replicate at 8B+; the passage-overlap heuristic's gains may likewise shrink at larger scale where baseline grounding is already strong.

7 Conclusion

We reported an empirical study of refinement-based methods for improving grounded RAG at small model scale, using Qwen3-4B on ALCE-ASQA (clean, 5-passage retrieval) and GaRAGe (noisy, 15-passage retrieval) with $N = 900$ per condition from 300 questions × 3 decoding seeds.

We showed that: (1) LLM Self-Refine actively degrades citation precision on clean retrieval (−9.37 pts NLI, $p < 0.01$) and its effect is benchmark-dependent—it slightly helps on noisy retrieval (+2.37 pts GaRAGe) for different reasons than grounding improvement. (2) A trivially cheap passage-overlap heuristic that triggers a targeted regeneration when the draft answer's content words do not appear in the passages avoids this failure mode and significantly improves grounding on distractor-rich benchmarks (+7.09 pts RFCP, $p < 0.01$; +11.45 pts NLI on ALCE vs Self-Refine with 85.4% blinded-judge win rate). It does not hurt clean-retrieval grounding. (3) STR-EM, the standard ASQA metric, is entirely blind to these effects—a metric-pathology finding in its own right.

For practitioners operating small models on noisy retrieval, the passage-overlap heuristic is the current best deployable grounding-refinement method we have evidence for: deterministic, auditable, training-free, and cheaper than Self-Refine while materially safer for citation precision. Follow-up work on token-level mechanistic attribution is reported in the companion paper.

Code, data, judge outputs, and evaluation scripts are available at `[repo URL]`.

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A Appendix: Practitioner's Guide — Should You Refine After the LLM?

This appendix translates our findings into a deployment-oriented decision tree for teams integrating RAG pipelines into production systems. We emphasize small-model settings ($\leq$ 8B parameters), noisy retrieval (10–20 passages), and domains where grounding is critical (legal, medical, compliance, financial investigations).

A.1 Decision tree: what to do after the LLM drafts

`IF Self-Refine (LLM-critiques-itself) is in your pipeline today:` → **Remove it.** Our evidence ($N = 300$ ALCE): -9.37 pts NLI citation precision on clean retrieval ($p < 0.01$), no significant gain on noisy retrieval. Additionally beats by +11.45 NLI points / 85.4% blinded-judge win rate against the passage-overlap heuristic on ALCE. Self-Refine is compute waste or actively harmful.
`IF your retrieval is clean (5 targeted passages, high top-1 retrieval score):` → **Do nothing after the LLM.** Baseline is already near-ceiling on grounding. Passage-overlap refinement $D - A = +2.08$ pts NLI on ALCE, CI includes 0—no significant gain, and refinement carries downside risk from Self-Refine-style inflation if you use LLM self-critique.
`IF your retrieval is noisy (10+ passages, mixed relevance):` → **Add passage-overlap heuristic refinement.** Cheap (20 lines of Python, one extra generation pass). On GaRAGe: +7.09 pts NLI citation precision, $p < 0.01$, significant across all three relevance strata. Deterministic, auditable, no extra models.
`IF you can't tell whether retrieval is clean or noisy:` → **Use always-on passage-overlap refinement** as a safe default. Our evidence shows the passage-overlap heuristic is non-harmful on clean retrieval (ties) and significantly beneficial on noisy retrieval. Cost: roughly $2-2.5\times$ per-query. Roll out the passage-overlap heuristic first; refine triggering later.

Figure 1: Decision tree for post-LLM refinement. Evidence references are to this paper's Phase 1 results.

A.2 Detecting noisy retrieval in production without ground truth

The decision tree requires knowing if retrieval is noisy. In production (no labels), several cheap proxies work:

- **Top-k retrieval score distribution.** If top-1 score $\gg$ top-10, retrieval is confident. Flat distribution signals noisy retrieval.
- **Number of passages retrieved.** More passages = more distractor risk; ≤ 5 passages $\approx$ clean regime.
- **Cross-source heterogeneity.** Single-source retrieval (one KB) is typically cleaner than multi-source (structured data + news + social).
- **Pairwise semantic similarity among top-k.** High average cosine = converging evidence; low average = contradictory/diffuse evidence.
- **Query specificity.** Entity-specific queries are clean; open-ended summarization queries are noisy.
- **Passage-overlap score as a diagnostic.** A low S_3 score on the baseline answer is itself a signal that retrieval was noisy (regardless of whether you trigger refinement).

None of these is perfect. In deployment, one pragmatic approach: compute several cheap proxies, combine into a "retrieval difficulty" score, and gate refinement on that score. Our passage-overlap heuristic approach effectively does this by using baseline-passage overlap as its signal.

A.3 Worked example: Anti-Money Laundering (AML)

As a concrete application, we walk through how the decision tree applies to common AML tasks at a financial institution. AML teams typically run small/specialized local models (data sovereignty requirements), face critical grounding requirements (regulatory scrutiny), and operate at scale (millions of transactions/alerts per day)—the exact regime our paper studies.

Table 4: AML task taxonomy and recommended post-LLM strategy per this paper's evidence.

AML Task	Retrieval Shape	Recommended Strategy
Alert rationale ("why did rule R-17 fire?")	Clean: 1–3 fired rules, customer profile, targeted context	**Baseline only.** Refinement doesn't significantly help; Self-Refine may hurt.
Regulatory threshold Q&A	Clean: targeted retrieval of 3–5 regulation sections	**Baseline only.** Same rationale.
SAR narrative drafting	**Noisy**: transactions + KYC + adverse media + internal notes; 20+ docs of wildly variable relevance	**Passage-overlap heuristic.**
Customer Due Diligence (CDD/EDD) summary	**Noisy**: registry + UBO chain + sanctions + adverse media, many distractors	**Passage-overlap heuristic.**
Typology classification	**Noisy**: case evidence + multiple typology definitions, only 1–2 apply	**Passage-overlap heuristic.**
Investigator case summary	**Noisy**: multi-year case history + prior investigator notes + external data	**Passage-overlap heuristic.**

Specific recommendations for AML practitioners.

1. **Remove any Self-Refine-style "polish pass"** from production copilots. Our evidence says it inflates answer length, adds distractor citations, and hurts grounding precision, particularly on cleanly retrieved cases.
2. **Add passage-overlap heuristic grounding checks** on noisy-retrieval tasks (SAR drafting, CDD, typology): compute lexical overlap between the draft answer and the source documents; when overlap is low, trigger a critique-and-regenerate pass. Our findings suggest ~ 7 pts NLI citation precision improvement on distractor-rich retrieval. S3 is deterministic and auditable (important for regulator review).
3. **Use NLI-based metrics, not keyword-coverage** when evaluating grounding improvements in A/B tests. We found STR-EM (substring-match metric) is completely blind to all refinement effects—a problem that would apply equally to any AML eval that uses edit-distance or token-overlap metrics against gold narratives.
4. **Caveat: our grounding task is "does claim appear in passage".** AML grounding is stricter—does the specific amount, date, entity, or relationship appear in an authoritative primary source (ledger, registry, contract) rather than a secondary source (summary, news)? Our methods do not distinguish primary vs. secondary sources; that is future work.
5. **Caveat: LLM-as-judge is development-only.** Regulatory defensibility in AML requires human-in-the-loop validation. Use LLM judge for method development; use human reviewers for compliance signoff and formal evaluations.

Innovation team activities suggested by this paper.

- Run an internal A/B test: baseline / Self-Refine / passage-overlap heuristic on $200-500$ historical SAR drafts or CDD summaries. Have senior analysts blind-rank for grounding quality. Replicate our protocol on your own data to calibrate expectations for your retrieval quality and model size.
- Build a "grounding QC" module that flags problematic drafts for human review using the passage-overlap signal S_3. Drafts below a calibrated overlap threshold get routed to an analyst; drafts above it can proceed.