RAG vs. GraphRAG: A Systematic Evaluation and Key Insights

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Abstract

Retrieval-Augmented Generation (RAG) enhances the performance of LLMs across various tasks by retrieving relevant information from external sources, particularly on text-based data. For structured data, such as knowledge graphs, GraphRAG has been widely used to retrieve relevant information. However, recent studies have revealed that structuring implicit knowledge from text into graphs can benefit certain tasks, extending the application of GraphRAG from graph data to general text-based data. Despite their successful extensions, most applications of GraphRAG for text data have been designed for specific tasks and datasets, lacking a systematic evaluation and comparison between RAG and GraphRAG on widely used text-based benchmarks. In this paper, we systematically evaluate RAG and GraphRAG on well-established benchmark tasks, such as Question Answering and Query-based Summarization. Our results highlight the distinct strengths of RAG and GraphRAG across different tasks and evaluation perspectives. Inspired by these observations, we investigate strategies to integrate their strengths to improve downstream tasks. Additionally, we provide an in-depth discussion of the shortcomings of current GraphRAG approaches and outline directions for future research.

1 Introduction

Retrieval-Augmented Generation (RAG) has emerged as a powerful approach to enhance downstream tasks by retrieving relevant knowledge from external data sources. It has achieved remarkable success in various real-world applications, such as healthcare (Xu et al., 2024), law (Wiratunga et al., 2024), finance (Zhang et al., 2023), and education (Miladi et al., 2024). This success has been further amplified with the advent of Large Language Models (LLMs), as integrating RAG with LLMs significantly improves their faithfulness by mitigating hallucinations, reducing privacy risks, and enhancing robustness (Zhao et al., 2023; Huang et al., 2023). In most existing RAG systems, retrieval is primarily conducted from text databases using lexical and semantic search.

Graphs, as a fundamental data structure, encode rich relational information and have been extensively utilized across real-world domains, including knowledge representation, social network analysis, and biomedical research (Wu et al., 2020; Ma and Tang, 2021; Wu et al., 2023). Motivated by this, GraphRAG has recently gained attention for retrieving graph-structured data, such as knowledge graphs (KGs) and molecular graphs (Han et al., 2024; Peng et al., 2024). Beyond leveraging existing graphs, GraphRAG has also demonstrated its effectiveness for text-based tasks after structuring implicit knowledge from text into graph representations, benefiting applications such as global summarization (Edge et al., 2024; Zhang et al., 2024), planning (Lin et al., 2024) and reasoning (Han et al., 2025).

While previous studies have demonstrated the potential of GraphRAG for text-based tasks by converting sequential text into graphs, most of them primarily focus on specific tasks and well-designed datasets. Consequently, the applicability of GraphRAG to broader, real-world text-based tasks remains unclear, particularly when compared to RAG, which has seen widespread adoption across diverse applications. This raises a critical question: *What are the advantages and disadvantages of applying GraphRAG to general text-based tasks compared to RAG?*

To bridge this gap, we systematically evaluate the performance of RAG and GraphRAG on general text-based tasks using widely adopted datasets, including Question Answering and Query-based Summarization. Specifically, we assess two representative GraphRAG methods: **(1)** Knowledge Graph-based GraphRAG (Liu, 2022), which extracts a Knowledge Graph (KG) from text and per-

forms retrieval solely based on the KG and **(2)** Community-based GraphRAG (Edge et al., 2024), which retrieves information not only from the constructed KG but also from hierarchical communities within the graph. For the Question Answering task, we conduct experiments on both single-hop and multi-hop QA under single-document and multi-document scenarios. Similarly, for the Query-based Summarization task, we evaluate both single-document and multi-document summarization to comprehensively assess the effectiveness of RAG and GraphRAG.

Based on our comprehensive evaluation, we conduct an in-depth analysis of the strengths and weaknesses of RAG and GraphRAG across different tasks. Our findings reveal that RAG and GraphRAG are complementary, each excelling in different aspects. For the Question Answering task, we observe that RAG performs better on single-hop questions and those requiring detailed information, while GraphRAG is more effective for multi-hop questions. In the Query-based Summarization task, RAG captures fine-grained details, whereas GraphRAG generates more diverse and multi-faceted summaries. Building on these insights, we investigate two strategies from different perspectives to integrate their unique strengths and enhance the overall performance. Our main contributions are as follows:

- **Systematical Evaluation** : This is the very first work to systematically evaluate and compare RAG and GraphRAG on text-based tasks using widely adopted datasets and evaluations.
- **Task-Specific Insights**: We provide an in-depth analysis of the distinct strengths of RAG and GraphRAG, demonstrating their complementary advantages across different types of queries and objectives.
- **Hybrid Retrieval Strategies:** Based on our findings on the unique strengths of RAG and GraphRAG, we propose two strategies to improve overall performance: (1) Selection, where queries are dynamically assigned to either RAG or GraphRAG based on their characteristics, and (2) Integration, where both methods are integrated to leverage their complementary strengths.
- **Challenges and Future Directions:** We discuss the limitations of current GraphRAG approaches and outline potential future research directions for broader applicability.

2 Related Works

2.1 Retrieval-Augmented Generation

Retrieval-Augmented Generation (RAG) has been widely applied to enhance the performance of Large Language Models (LLMs) by retrieving relevant information from external sources, addressing the limitation of LLMs' restricted context windows, improving factual accuracy, and mitigating hallucinations (Fan et al., 2024; Gao et al., 2023). Most RAG systems primarily process text data by first splitting it into chunks (Finardi et al., 2024). When a query is received, RAG retrieves relevant chunks either through lexical search (Ram et al., 2023) or by computing semantic similarity (Karpukhin et al., 2020), embeddings both the query and text chunks into a shared vector space. Advanced techniques, such as pre-retrieval processing (Ma et al., 2023; Zheng et al., 2023a) and post-retrieval processing (Dong et al., 2024; Xu et al., 2023), as well as fine-tuning strategies (Li et al., 2023), have further enhanced RAG's effectiveness across various domains, including QA) (Yan et al., 2024), dialogue generation (Izacard et al., 2023), and text summarization (Jiang et al., 2023).

Several studies have evaluated the effectiveness of RAG systems across various tasks (Yu et al., 2024; Chen et al., 2024; Es et al., 2023), such as multi-hop question answering (Tang and Yang, 2024), biomedical question answering (Xiong et al., 2024), and text generation (Liu et al., 2023). However, no existing study has simultaneously and systematically evaluated and compared RAG and GraphRAG on these general text-based tasks.

2.2 Graph Retrieval-Augmented Generation

While RAG primarily processes text data, many real-world scenarios involve graph-structured data, such as knowledge graphs (KGs), social graphs, and molecular graphs (Xia et al., 2021; Ma and Tang, 2021). GraphRAG (Han et al., 2024; Peng et al., 2024) aims to retrieve information from various types of graph-structured data. The inherent structure of graphs enhances retrieval by capturing relationships between connected nodes. For example, hyperlinks between documents can improve retrieval effectiveness in question answering tasks(Li et al., 2022). Currently, most GraphRAG studies focus on retrieving information from existing KGs for downstream tasks such as KG-based QA (Tian et al., 2024; Yasunaga et al., 2021) and Fact-Checking (Kim et al., 2023).

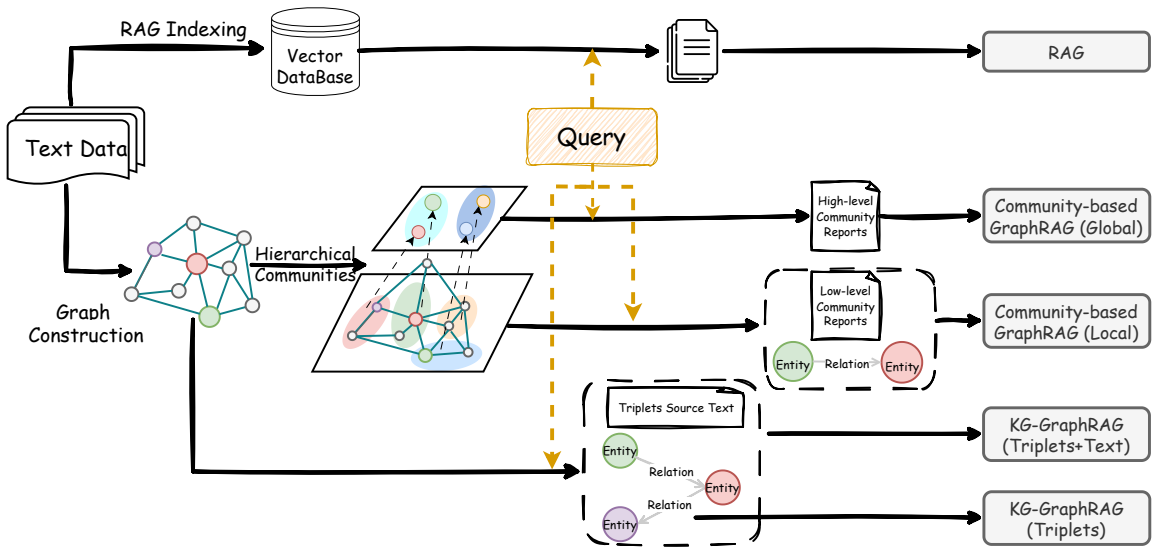


Figure 1: The illustration of RAG, KG-based GraphRAGs and Community-based GraphRAGs.

Despite leveraging the existing graphs, recent studies have explored incorporating graph construction into GraphRAG to enhance text-based tasks. For example, Dong et al. (2024) construct document graphs using Abstract Meaning Representation (AMR) to improve document ranking. Edge et al. (2024) construct graphs from documents using LLMs, where nodes represent entities and edges capture relationships between them. Based on these graphs, they generate hierarchical communities and corresponding community summaries or reports. Their approach focuses on the global query summarization task, retrieving information from both the constructed graphs and their hierarchical communities. Additionally, Han et al. (2025) propose an iterative graph construction approach using LLMs to improve reasoning tasks.

These studies highlight the potential of GraphRAG in processing text-based tasks by constructing graphs from textual data. However, their focus is limited to specific tasks and evaluation settings. It remains unclear how GraphRAG performs on general text-based tasks compared to RAG. More importantly, when and how should GraphRAG be applied to such tasks for optimal effectiveness? Our work aims to bridge this gap by systematically evaluating GraphRAG and comparing it with RAG on general text-based tasks.

3 Evaluation Methodology

In this section, we introduce the details of our evaluation framework. We primarily evaluate one representative RAG system and two representative GraphRAG systems, as illustrated in Figure 1.

3.1 RAG

We adopt a representative semantic similarity-based retrieval approach as our RAG method (Karpukhin et al., 2020). Specifically, we first split the text into chunks, each containing approximately 256 tokens. For indexing, we use OpenAI's text-embedding-ada-002 model, which has demonstrated effectiveness across various tasks (Nussbaum et al., 2024). For each query, we retrieve chunks with Top-10 similarity scores. To generate responses, we employ two open-source models of different sizes: Llama-3.1-8B-Instruct and Llama-3.1-70B-Instruct (Dubey et al., 2024).

For single-document tasks, we generate a separate RAG system for each document, ensuring that queries corresponding to a specific document are processed within its respective indexed chunk pool. For multi-document tasks, we use a shared RAG system by indexing all documents together.

3.2 GraphRAG

We select two representative GraphRAG methods for a comprehensive evaluation, as shown in Figure 1, namely KG-based GraphRAG and Community-based GraphRAG.

In the KG-based GraphRAG (KG-GraphRAG) (Liu, 2022), a knowledge graph is first constructed from text chunks using LLMs through triplet extraction. When a query is received, its entities are extracted and matched to those in the constructed KG using LLMs. The retrieval process then traverses the graph from the matched entities and gathers triplets *(head, relation, tail)* from their multi-hop neighbors as the retrieved

content. Additionally, for each triplet, we can retrieve the corresponding text associated with it. We define two variants of KG-GraphRAG: **(1)** *KG-GraphRAG (Triplets)*, which retrieves only the triplets, and **(2)** *KG-GraphRAG (Triplets+Text)*, which retrieves both the triplets and their associated source text. We implement the KG-GraphRAG methods using LlamaIndex (Liu, 2022) [1].

For the Community-based GraphRAG (Edge et al., 2024), in addition to generating KGs using LLMs, hierarchical communities are constructed using graph community detection algorithms, as shown in Figure 1. Each community is associated with a corresponding text summary or report, where lower-level communities contain detailed information from the original text. The higher-level communities further provide summaries of the lower-level communities. Due to the hierarchical community structure, there are two primary retrieval methods for retrieving relevant information given a query: **Local Search and Global Search**. In Local Search, entities, relations, their descriptions, and lower-level community reports are retrieved based on entity matching between the query's extracted entities and the constructed graph. We refer to this method as *Community-GraphRAG (Local)*. In Global Search, only high-level community summaries are retrieved based on semantic similarity to the query. We refer to this method as *Community-GraphRAG (Global)*. The Community-GraphRAG methods are implemented using Microsoft GraphRAG (Edge et al., 2024)[2]. In this paper, we primarily use GPT-4o-mini to construct the graphs. The results using GPT-4o are also provided in Appendix A.10.

To ensure a fair comparison, we adopt the same settings for both RAG and GraphRAG methods, including the chunking strategy, embedding model, and generation LLMs. We select two representative RAG tasks, i.e., Question Answering and Query-based Summarization, to evaluate RAG and GraphRAG simultaneously.

4 Question Answering

QA is one of the most widely used tasks for evaluating the performance of RAG systems. QA tasks come in various forms, such as single-hop QA, multi-hop QA, and open-domain QA (Wang, 2022). To systematically assess the effectiveness of RAG and GraphRAG in these tasks, we evaluate them on widely used QA datasets and employ standard evaluation metrics.

4.1 Datasets and Evaluation Metrics

To comprehensively evaluate the performance of GraphRAG on general QA tasks, we select four widely used datasets that cover different perspectives. For the single-hop QA task, we select the Natural Questions (NQ) dataset (Kwiatkowski et al., 2019). For the multi-hop QA task, we select HotPotQA (Yang et al., 2018) and MultiHop-RAG (Tang and Yang, 2024) datasets. The MultiHop-RAG dataset categorizes queries into four types: Inference, Comparison, Temporal, and Null queries. To further analyze the performance of RAG and GraphRAG at a finer granularity, we also include NovelQA (Wang et al., 2024a), which contains 21 different types of queries. For more details, please refer to Appendix A.1.1. We use Precision (P), Recall (R), and F1-score as evaluation metrics for the NQ and HotPotQA datasets, while accuracy is used for the MultiHop-RAG and NovelQA datasets following their original papers.

4.2 QA Main Results

The performance comparison for the NQ and HotPotQA datasets is presented in Table 1, while that of MultiHop-RAG is shown in Table 2. The overall and average performance are reported as weighted averages. Due to space constraints, partial results of NovelQA with the Llama 3.1-8B model are shown in Table 3, with the full results available in Appendix A.2. Based on these results, we make the following observations:

1. **RAG excels on detailed single-hop queries**. RAG performs well on single-hop queries and queries that require detailed information. This is evident from its performance on the single-hop dataset (NQ) as well as the single-hop (sh) and detail-oriented (dtl) queries in the NovelQA dataset, as shown in Table 1 and Table 3.
2. **GraphRAG, particularly Community-GraphRAG (Local), excels on multi-hop queries.** For instance, it achieved the best performance on both the HotPotQA and MultiHop-RAG datasets. Although its overall performance on the NovelQA dataset is lower than that of RAG, it still performs well on the multi-hop (mh) queries in NovelQA dataset.
3. **Community-GraphRAG (Global) often struggles on QA tasks**. This is due to the global search retrieves only high-level communities,

[1] https://www.llamaindex.ai/

[2] https://microsoft.github.io/graphrag

Table 1: Performance comparison (%) on NQ and Hotpot datasets. The best results are highlighted in bold, and the second-best results are underlined.

Method	NQ						Hotpot					
	Llama 3.1-8B			Llama 3.1-70B			Llama 3.1-8B			Llama 3.1-70B		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	**71.70**	**63.93**	**64.78**	**74.55**	**67.82**	**68.18**	62.32	60.47	60.04	66.34	63.99	63.88
KG-GraphRAG (Triplets only)	40.09	33.56	34.28	37.84	31.22	28.50	26.88	24.81	25.02	32.59	30.63	30.73
KG-GraphRAG (Triplets+Text)	58.36	48.93	50.27	60.91	52.75	53.88	45.22	42.85	42.60	51.44	48.99	48.75
Community-GraphRAG (Local)	69.48	62.54	63.01	71.27	65.46	65.44	**64.14**	**62.08**	**61.66**	**67.20**	**64.89**	**64.60**
Community-GraphRAG (Global)	60.76	54.99	54.48	61.15	55.52	55.05	45.72	47.60	45.16	48.33	48.56	46.99

Table 2: Performance comparison (%) on the MultiHop-RAG dataset across different query types.

Method	LLama 3.1-8B					Llama 3.1-70B				
	Inference	Comparison	Null	Temporal	Overall	Inference	Comparison	Null	Temporal	Overall
RAG	**92.16**	57.59	96.01	30.70	67.02	**94.85**	56.31	91.36	25.73	65.77
KG-GraphRAG (Triplets only)	55.76	22.55	**98.67**	18.70	41.24	76.96	32.36	**94.35**	19.55	50.98
KG-GraphRAG (Triplets+Text)	67.40	34.70	97.34	17.15	48.51	85.91	35.98	86.38	21.61	54.58
Community-GraphRAG (Local)	86.89	60.63	80.07	50.60	**69.01**	92.03	60.16	88.70	49.06	**71.17**
Community-GraphRAG (Global)	89.34	**64.02**	19.27	**53.34**	64.40	89.09	**66.00**	13.95	**59.18**	65.69

Table 3: Performance comparison (%) on the NovelQA dataset across different query types with LLama 3.1-8B.

RAG									KG-GraphRAG (Triplets+Text)								
	chara	mean	plot	relat	settg	span	times	avg		chara	mean	plot	relat	settg	span	times	avg
mh	68.75	52.94	58.33	75.28	92.31	64.00	33.96	47.34	mh	52.08	52.94	44.44	55.06	69.23	64.00	28.61	38.37
sh	69.08	62.86	66.11	75.00	78.35	-	-	68.73	sh	36.84	45.71	40.17	87.50	36.08	-	-	39.93
dtl	64.29	45.51	78.57	10.71	83.78	-	-	55.28	dtl	38.57	30.90	42.86	21.43	32.43	-	-	33.60
avg	67.78	50.57	67.37	60.80	80.95	64.00	33.96	57.12	avg	40.00	36.23	41.09	49.60	38.10	64.00	28.61	37.80
Community-GraphRAG (Local)									**Community-GraphRAG (Global)**								
	chara	mean	plot	relat	settg	span	times	avg		chara	mean	plot	relat	settg	span	times	avg
mh	68.75	64.71	55.56	67.42	92.31	52.00	35.83	47.01	mh	54.17	58.82	55.56	56.18	53.85	68.00	20.59	34.39
sh	59.87	58.57	65.69	87.50	64.95	-	-	63.43	sh	45.39	50.00	55.65	87.50	38.14	-	-	49.65
dtl	54.29	37.64	62.50	25.00	70.27	-	-	46.88	dtl	28.57	29.78	32.14	87.50	40.54	-	-	30.89
avg	60.00	44.91	64.05	59.20	68.71	52.00	35.83	53.03	avg	42.59	36.98	51.66	52.00	40.14	68.00	20.59	39.17

leading to a loss of detailed information. This is particularly evident from its lower performance on detail-oriented queries in the NovelQA dataset. Additionally, Community-GraphRAG (Global) tends to hallucinate in QA tasks, as shown by its poor performance on Null queries in the MultiHop-RAG dataset, which should ideally be answered as 'insufficient information.' However, this summarization approach may be beneficial for queries that require comparing different topics or understanding their temporal ordering, such as Comparison and Temporal queries in the MultiHop-RAG dataset (Table 2).

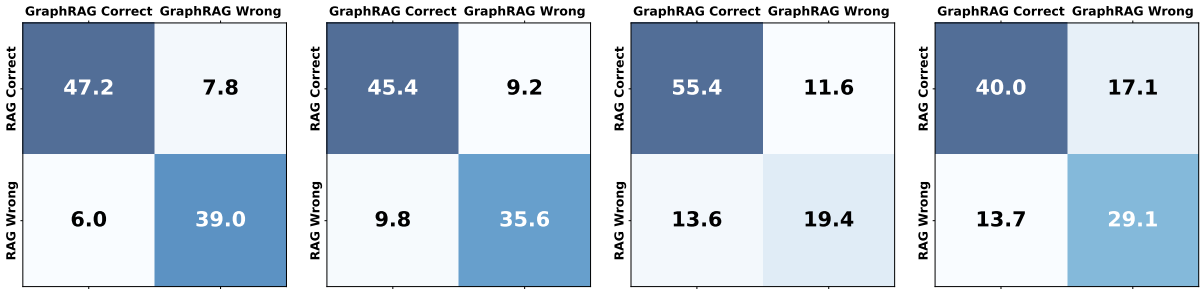
4. **KG-based GraphRAG also generally underperform on QA tasks**. This is because it retrieves information solely from the constructed knowledge graph, which contains only entities and their relations. However, the extracted entities and relations may be incomplete, leading to gaps in the retrieved information. To verify this, we calculated the retrieval accuracy in Appendix A.3. We found that only around 65.8% of answer entities exist in the constructed KG for the Hotpot dataset and 65.5% for the NQ dataset. These findings highlight a key limitation in KG-based retrieval and suggest the need for improved KG construction methods to enhance graph completeness for QA.

To better illustrate the differences, we also provide case studies comparing the retrieved content of RAG and GraphRAG in Appendix A.4.

4.3 Comparative QA Analysis

In this section, we conduct a detailed analysis of the behavior of RAG and GraphRAG, focusing on their strengths and weaknesses. In the following discussion, we refer to Community-GraphRAG (Local) as GraphRAG, as it demonstrates performance comparable to RAG. We categorize queries into four groups: **(1)** Queries correctly answered by both methods, **(2)** Queries correctly answered only by RAG (RAG-only), **(3)** Queries correctly answered only by GraphRAG (GraphRAG-only), and **(4)** Queries answered incorrectly by both methods.

The confusion matrices representing these four groups using the Llama 3.1-8B model are shown in Figure 2. Notably, the proportions of queries correctly answered exclusively by GraphRAG and RAG are significant. For example, 13.6% of



(a) NQ (b) Hotpot (c) MultiHop-RAG (d) NovelQA

Figure 2: Confusion matrices comparing GraphRAG and RAG correctness across datasets using Llama 3.1-8B.

queries are GraphRAG-only, while 11.6% are RAG-only on MultiHop-RAG dataset. This phenomenon highlights the complementary properties of RAG and GraphRAG, and each method has its own strengths and weaknesses. Therefore, *leveraging their unique advantages has the potential to improve overall performance*.

4.4 Improving QA Performance

Building on the complementary properties of RAG and GraphRAG, we investigate the following two strategies to enhance overall QA performance.

Strategy 1: RAG vs. GraphRAG Selection. In Section 4.2, we observe that RAG generally performs well on single-hop queries and those requiring detailed information, while GraphRAG (Community-GraphRAG (Local)) excels in multi-hop queries that require reasoning. Therefore, we hypothesize that RAG is well-suited for fact-based queries, which rely on direct retrieval and detailed information, whereas GraphRAG is more effective for reasoning-based queries that involve chaining multiple facts together. Therefore, given a query, we employ a classification mechanism to determine whether it is fact-based or reasoning-based. Each query is then assigned to either RAG or GraphRAG based on the classification results. Specifically, we leverage the in-context learning ability of LLMs for classification (Dong et al., 2022; Wei et al., 2023). Further details and prompts can be found in Appendix A.5. In this strategy, either RAG or GraphRAG is selected for each query, and we refer to this strategy as **Selection**.

Strategy 2: RAG and GraphRAG Integration. We also explore the **Integration** strategy to leverage the complementary strengths of RAG and GraphRAG. Both RAG and GraphRAG retrieve information for a query simultaneously. The retrieved results are then concatenated and fed into the generator to produce the final output.

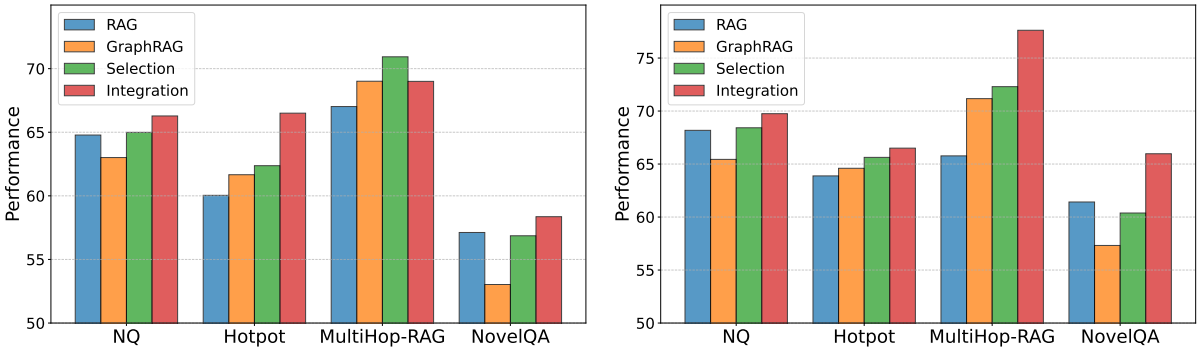
We conduct experiments to verify the effectiveness of the two proposed strategies. Specifically, we evaluate overall performance across all selected datasets. For the MultiHop-RAG and NovelQA datasets, we use the overall accuracy, while for the NQ and HotPotQA datasets, we use the F1 score as the evaluation metric. The results are shown in Figure 3 and Appendix A.6. From these results, we observe that **both strategies generally enhance overall performance**. For example, on the MultiHop-RAG dataset with Llama 3.1-70B, Selection and Integration improve the best method by 1.1% and 6.4%, respectively. When comparing the Selection and Integration strategies, the Integration strategy usually achieves higher performance than the Selection strategy. However, Selection strategy processes each query using either RAG or GraphRAG, making it more efficient. In contrast, Integration strategy yields better performance but requires each query to be processed by both RAG and GraphRAG, increasing computational cost.

5 Query-Based Summarization

Query-based summarization tasks are widely used to evaluate the performance of RAG systems (Ram et al., 2023; Yu et al., 2023). GraphRAG has also demonstrated its effectiveness in summarization tasks (Edge et al., 2024). However, Edge et al. (2024) only evaluate its effectiveness on the global summarization task and rely on LLM-as-a-Judge (Zheng et al., 2023b) for performance assessment. In Section 5.3, we show that the LLM-as-a-Judge evaluation method for summarization tasks introduces position bias, which can impact the reliability of results. A systematic comparison of RAG and GraphRAG on general query-based summarization across widely used datasets remains unexplored. To address this gap, we conduct a comprehensive evaluation in this section, leveraging widely used datasets and evaluation metrics.

5.1 Datasets and Evaluation Metrics

We adopt two widely used single-document query-based summarization datasets, SQuALITY (Wang et al., 2022) and QMSum (Zhong et al., 2021),



(a) Llama3.1-8B (b) Llama3.1-70B

Figure 3: Overall QA performance comparison of different methods.

and two multi-document query-based summarization datasets, ODSum-story and ODSum-meeting (Zhou et al., 2023), for our evaluation. Unlike the LLM-generated global queries used in the unreleased datasets of Edge et al. (2024), most queries in the selected datasets focus on specific roles or events. Since these datasets contain one or more human-written ground truth summaries for each query, we use ROUGE-2 (Lin, 2004) and BERTScore (Zhang et al., 2019) as evaluation metrics to measure lexical and semantic similarity between the predicted and ground truth summaries.

5.2 Summarization Experimental Results

We evaluate both the KG-based and Community-based GraphRAG methods, along with the Integration strategy discussed in Section 4.4. The results of Llama3.1-8B model on Query-based single document summarization and multiple document summarization are shown in Table 4 and Table 5, respectively. The results of Llama3.1-70B are shown in Appendix A.7. Based on these results, we can make the following observations:

1. **RAG generally performs well on query-based summarization tasks**. This is particularly true on multi-document summarization datasets.
2. **KG-based GraphRAG benefit from combining triplets with their corresponding text**. This improves performance by incorporating more details, making predictions closer to the human-written ground truth summaries.
3. **Community-based GraphRAG performs better with the Local search method**. Local search retrieves entities, relations, and low-level communities, while the Global search method retrieves only high-level summaries. This demonstrates the importance of detailed information in the selected datasets.
4. **The Integration strategy often performs comparably to RAG alone**, as explained in Appendix A.6.

5.3 Position Bias in Existing Evaluation

From the results in Section 5.2, the Community-based GraphRAG, particularly with global search, generally underperforms compared to RAG on the selected datasets. This contrasts with the findings of Edge et al. (2024), where Community-based GraphRAG with global search outperformed both local search and RAG. There are two key differences between our evaluation and Edge et al. (2024). First, their study primarily focuses on global summarization, which captures the overall information of an entire corpus, whereas the selected datasets in our evaluation contain queries related to specific roles or events. Second, Edge et al. (2024) assess performance by comparing RAG and GraphRAG outputs using LLM-as-a-Judge without ground truth, whereas we evaluate results against ground truth summaries using ROUGE and BERTScore. These metrics emphasize similarity to the reference summaries, which often contain more detailed information.

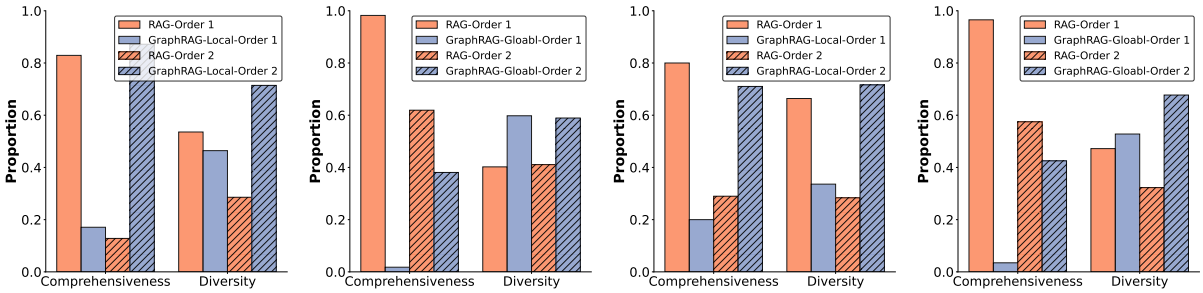
We further conduct an evaluation following Edge et al. (2024), using the LLM-as-a-Judge method from two perspectives: Comprehensiveness and Diversity. Comprehensiveness measures how well the summary covers details of the query, while Diversity evaluates whether the answer provides a broad and globally inclusive perspective. Full prompt details are in Appendix A.8. Specifically, we input summaries from RAG and GraphRAG into the prompt and ask the LLM to choose the better one for each metric. To account for position bias, we evaluate two orderings: Order 1 (O1) places the RAG summary first, and Order 2 (O2) places GraphRAG first. We report the proportion of times each method is preferred, where a higher proportion indicates stronger performance as judged by the LLM.

Table 4: The performance of query-based single document summarization task using Llama3.1-8B.

Method	SQuALITY						QMSum					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	15.09	8.74	10.08	74.54	81.00	77.62	21.50	**3.80**	6.32	**81.03**	84.45	**82.69**
KG-GraphRAG (Triplets only)	11.99	6.16	7.41	82.46	84.30	83.17	13.71	2.55	4.15	80.16	82.96	81.52
KG-GraphRAG (Triplets+Text)	15.00	**9.48**	10.52	**84.37**	**85.88**	**84.92**	16.83	3.32	5.38	80.92	83.64	82.25
Community-GraphRAG (Local)	**15.82**	8.64	10.10	83.93	85.84	84.66	20.54	3.35	5.64	80.63	84.13	82.34
Community-GraphRAG (Global)	10.23	6.21	6.99	82.68	84.26	83.30	10.54	1.97	3.23	79.79	82.47	81.10
Integration	15.69	9.32	**10.67**	74.56	81.22	77.73	**21.97**	**3.80**	**6.34**	80.89	**84.47**	82.63

Table 5: The performance of query-based multiple document summarization task using Llama3.1-8B.

Method	ODSum-story						ODSum-meeting					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	**15.39**	8.44	**9.81**	**83.87**	**85.74**	**84.57**	15.50	**6.43**	**8.77**	**83.12**	**85.84**	**84.45**
KG-GraphRAG (Triplets only)	11.02	5.56	6.62	82.09	83.91	82.77	11.64	4.87	6.58	81.13	84.32	82.69
KG-GraphRAG (Triplets+Text)	9.19	5.82	6.22	79.39	83.30	81.03	11.97	4.97	6.72	81.50	84.41	82.92
Community-GraphRAG (Local)	13.84	7.19	8.49	83.19	85.07	83.90	15.65	5.66	8.02	82.44	85.54	83.96
Community-GraphRAG (Global)	9.40	4.47	5.46	81.46	83.54	82.30	11.44	3.89	5.59	81.20	84.50	82.81
Integration	14.77	**8.55**	9.53	83.73	85.56	84.40	**15.69**	6.15	8.51	82.87	85.81	84.31



(a) QMSum Local (b) QMSum Global (c) ODSum-story Local (d) ODSum-story Global

Figure 4: Comparison of LLM-as-a-Judge evaluations for RAG and GraphRAG. "Local" refers to the evaluation of RAG vs. GraphRAG-Local, while "Global" refers to RAG vs. GraphRAG-Global.

The results of RAG vs. GraphRAG (Local) and RAG vs. GraphRAG (Global) on the QMSum and ODSum-story datasets are presented in Figure 4. More result can be found in Appendix A.9. We can make the following observations: (1) **Position bias (Shi et al., 2024; Wang et al., 2024b) is evident in the LLM-as-a-Judge evaluations for summarization task**, as changing the order of the two methods significantly affects the predictions. This effect is particularly strong in the comparison between RAG and GraphRAG (Local), where the LLMs make completely opposite decisions depending on the order, as shown in Figures 4a and 4c. However, (2) Comparison between RAG and GraphRAG (Global): While the proportions vary, RAG consistently outperforms GraphRAG (Global) in Comprehensiveness but underperforms in Diversity as shown in Figures 4b and 4d. This result suggests that **Community-based GraphRAG with Global Search focuses more on the global aspects of whole corpus, whereas RAG captures more detailed information.**

In addition to performance comparisons, we also include a time analysis of indexing, retrieval, and generation, as well as token and storage analyses for both methods in Appendix A.11, providing further insights into their practical trade-offs.

6 Conclusion

In this paper, we systematically evaluate and compare RAG and GraphRAG on general text-based tasks. Our analysis reveals the distinct strengths of RAG and GraphRAG in QA and query-based summarization, as well as evaluation challenges in summarization tasks, providing valuable insights for future research. Building on these findings, we propose two strategies to enhance QA performance. Future work can explore improving GraphRAG through better graph construction or developing novel approaches to combine RAG and GraphRAG methods for both effectiveness and efficiency.

Limitations

In this paper, we evaluate and compare RAG and GraphRAG on Question Answering and Query-based Summarization tasks. Future work can extend this study to additional tasks to further assess the strengths and applicability of GraphRAG. For example, tasks such as planning (Wu et al., 2024) and mathematical reasoning (Feng et al., 2021) have been shown to benefit from graph representations. However, the distinct advantages and limitations of RAG and GraphRAG in these settings remain to be systematically explored. Additionally, the graph construction in all GraphRAG methods explored in this work relies on LLM-based construction, where LLMs extract entities and relations. However, other graph construction models designed for text processing exist and can be investigated in future studies. Finally, we only use the basic retriever for RAG and GraphRAG. There are also other retrievers such as GNN-based retrievers and LLM-based retrievers for GraphRAG. We do not use GNN-based or LLM-based retrieval methods due to limitations in our setting. GNN-based retrievers require node-level supervision, which is unavailable in our dynamically constructed and often incomplete graphs. LLM-based retrievers typically rely on fixed relation types, whereas our graphs contain diverse and open-ended relations. To ensure a fair and consistent comparison between RAG and GraphRAG, we adopt a simple retrieval approach. Nonetheless, exploring how advanced retrieval strategies can be adapted to dynamically constructed KGs in GraphRAG is an interesting direction for future work.

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A Appendix

A.1 Dataset

In this section, we introduce the used datasets in the question answering tasks and query-based summarization tasks.

A.1.1 Question Answering

In the QA tasks, we use the following four widely used datasets:

- **Natural Questions (NQ)** (Kwiatkowski et al., 2019): The NQ dataset is a widely used benchmark for evaluating open-domain question answering systems. Introduced by Google, it consists of real user queries from Google Search with corresponding answers extracted from Wikipedia. Since it primarily contains single-hop questions, we use NQ as the representative dataset for single-hop QA. We treat NQ as a single-document QA task, where multiple questions are associated with each document. Accordingly, we build a separate RAG system for each document in the dataset.

- **Hotpot** (Yang et al., 2018): HotpotQA is a widely used multi-hop question dataset that provides 10 paragraphs per question. The dataset includes varying difficulty levels, with easier questions often solvable by LLMs. To ensure a more challenging evaluation, we randomly selected 1,000 hard bridging questions from the development set of HotpotQA. Additionally, we treat HotpotQA as a multi-document QA task and build a single RAG system to handle all questions.

- **MultiHop-RAG** (Tang and Yang, 2024): MultiHop-RAG is a QA dataset designed to evaluate retrieval and reasoning across multiple documents with metadata in RAG pipelines. Constructed from English news articles, it contains 2,556 queries, with supporting evidence distributed across 2 to 4 documents. The dataset includes four query types: Inference queries, which synthesize claims about a bridge entity to identify it; Comparison queries, which compare similarities or differences and typically yield "yes" or "no" answers; Temporal queries, which examine event ordering with answers like "before" or "after"; and Null queries, where no answer can be derived from the retrieved documents. It is also a multi-document QA task.

- **NovelQA** (Wang et al., 2024a): NovelQA is a benchmark designed to evaluate the long-text understanding and retrieval ability of LLMs using manually curated questions about English novels exceeding 50,000 words. The dataset includes queries that focus on minor details or require cross-chapter reasoning, making them inherently challenging for LLMs. It covers various query types such as details, multi-hop, single-hop, character, meaning, plot, relation, setting, span, and times. Key challenges highlighted by NovelQA include grasping abstract meanings (meaning questions), understanding nuanced relationships (relation questions), and tracking temporal sequences and spatial extents (span and time questions), emphasizing the difficulty of maintaining and applying contextual information across long narratives. We use it for single-document QA task.

A.1.2 Query-based Summarization

In the Query-based Summarization tasks, we adopt the following four widely used datasets:

- **SQuALITY** (Wang et al., 2022): SQuALITY (Summary-format QUestion Answering with Long Input Texts) is a question-focused, long-document, multi-reference summarization dataset. It consists of short stories from Project Gutenberg, each ranging from 4,000 to 6,000 words. Each story is paired with five questions, and each question has four reference summaries written by Upwork writers and NYU undergraduates. SQuALITY is designed as a single-document summarization task, making it a valuable benchmark for evaluating summarization models on long-form content.

- **QMSum** (Zhong et al., 2021): QMSum is a human-annotated benchmark for query-based, multi-domain meeting summarization, containing 1,808 query-summary pairs from 232 meetings across multiple domains. We use QMSum as a single-document summarization task in our evaluation.

- **ODSum** (Zhou et al., 2023): The ODSum dataset is designed to evaluate modern summarization models in multi-document contexts and consists of two subsets: ODSum-story and ODSum-meeting. ODSum-story is derived from the SQuALITY dataset, while ODSum-meeting is constructed from QMSum. We use both ODSum-story and ODSum-meeting for the multi-document summarization task in our evaluation.

A.2 More results on NovelQA dataset

In this section, we present the missing results for the NovelQA dataset from the main sections. These include the performance of KG-GraphRAG (Triplets) with LLaMA 3.1-8B (Table 6), RAG with LLaMA 3.1-70B (Table 7), KG-GraphRAG (Triplets) with LLaMA 3.1-70B (Table 8), KG-GraphRAG (Triplets+Text) with LLaMA 3.1-70B (Table 9), Community-GraphRAG (Local) with LLaMA 3.1-70B (Table 10), and Community-GraphRAG (Global) with LLaMA 3.1-70B (Table 11).

Table 6: The performance of KG-GraphRAG (Triplets) with Llama 3.1-8B model on NovelQA dataset.

KG-GraphRAG(Triplet)	character	meaning	plot	relat	settg	span	times	avg
mh	31.25	17.65	41.67	50.56	38.46	64	26.47	32.89
sh	35.53	45.71	30.54	62.5	27.84	-	-	33.75
dtl	31.43	24.72	35.71	17.86	27.03	-	-	27.37
avg	33.7	29.81	32.63	44	28.57	64	26.47	31.88

Table 7: The performance of RAG with Llama 3.1-70B model on NovelQA dataset.

RAG	character	meaning	plot	relat	settg	span	times	avg
mh	64.58	82.35	77.78	69.66	84.62	36	36.63	48.5
sh	70.39	70	76.57	75	83.51	-	-	75.27
dtl	60	51.12	76.79	67.86	83.78	-	-	61.25
avg	66.67	58.11	76.74	69.6	83.67	36	36.63	61.42

Table 8: The performance of KG-GraphRAG (Triplets) with Llama 3.1-70B model on NovelQA dataset.

KG-GraphRAG (Triplets)	character	meaning	plot	relat	settg	span	times	avg
mh	50	76.47	75	43.82	76.92	24	22.46	33.72
sh	52.63	62.86	55.23	12.5	50.52	-	-	54.06
dtl	35.71	26.97	39.29	53.57	37.84	-	-	33.6
avg	47.78	39.62	54.68	44	49.66	24	22.46	41.18

Table 9: The performance of KG-GraphRAG (Triplets+Text) with Llama 3.1-70B model on NovelQA dataset.

KG-GraphRAG (Triplets+Text)	character	meaning	plot	relat	settg	span	times	avg
mh	56.25	58.82	63.89	51.69	84.62	24	21.39	33.72
sh	51.97	61.43	55.65	50	50.52	-	-	54.42
dtl	34.29	25.28	41.07	50	37.84	-	-	32.52
avg	48.15	36.98	54.08	51.2	50.34	24	21.39	41.05

A.3 Retrieval accuracy of different methods

In this subsection, we compare the retrieval accuracy of various methods. Since there is no ground-truth label for the retrieval step, we evaluate effectiveness by reporting retrieval accuracy, defined as the proportion of cases where the ground-truth answer appears in the retrieved content. We conduct this evaluation on the Hotpot and NQ datasets.

Table 10: The performance of Community-GraphRAG (Local) with Llama 3.1-70B model on NovelQA dataset.

Community-GraphRAG (Local)	character	meaning	plot	relat	settg	span	times	avg
mh	77.08	70.59	63.89	77.53	92.31	28	32.35	46.68
sh	68.42	71.43	74.9	62.5	74.23	-	-	72.44
dtl	55.71	37.08	69.64	64.29	75.68	-	-	51.49
avg	66.67	48.3	72.81	73.6	76.19	28	32.35	57.32

Table 11: The performance of Community-GraphRAG (Global) with Llama 3.1-70B model on NovelQA dataset.

Community-GraphRAG (Global)	character	meaning	plot	relat	settg	span	times	avg
mh	47.92	58.82	55.56	57.3	61.54	16	35.83	41.53
sh	42.76	42.86	54.39	25	40.21	-	-	47
dtl	24.29	22.47	32.14	50	35.14	-	-	27.64
avg	38.89	30.19	50.76	53.6	40.82	16	35.83	40.21

Table 12: Retrieval accuracy of different methods on Hotpot and NQ datasets

Method	Hotpot	NQ
RAG	0.886	0.867
KG-GraphRAG(Triplets only)	0.392	0.3218
KG-GraphRAG(Triplets+Text)	0.698	0.615
Community-GraphRAG (Local)	0.6753	0.422
Community-GraphRAG (Global)	0.886	0.833

As shown in the Table 12, KG-GraphRAG (Triplets only) achieves relatively low retrieval accuracy, particularly on NQ. This is primarily due to the incompleteness of the constructed knowledge graphs—only 65.8% of answer entities exist in the HotpotQA KG, and 65.5% in the NQ KG. In contrast, Community-GraphRAG, which leverages community-level summarization, demonstrates significantly better retrieval performance.

These findings highlight several potential directions for improvement:

1. Enhancing KG construction to increase entity and relation coverage.
2. Combining structured graph information with raw text to improve retrieval robustness and completeness.

A.4 Case studies for the question answering task

In this section, we present examples where RAG fails but GraphRAG succeeds. In Case 1 (Figure 5), RAG fails because it does not retrieve all the relevant chunks required for answering the multi-hop reasoning question. KG-RAG also fails due to missing information during knowledge graph construction. However, Community-GraphRAG is able to answer correctly by leveraging community-level summarizations that capture the necessary context. In Case 2 (Figure 6), both KG-GraphRAG and Community-GraphRAG succeed because they capture the reasoning chain—either through explicit graph paths or through summarization within the same community. In contrast, RAG fails due to insufficient retrieved information.

A.5 RAG vs. GraphRAG Selection

We classify QA queries into Fact-based and Reasoning-based queries. Fact-based queries are processed using RAG, while Reasoning-based queries are handled by GraphRAG. The Query Classification prompt is shown in Figure 7.

A.6 RAG and GraphRAG Integration

In this section, we explore the effect of integrating RAG and GraphRAG for the question answering task. Specifically, we concatenate the retrieved results from both RAG and GraphRAG before passing them to

Case 1

Question: Alexander Kerensky was defeated and destroyed by the Bolsheviks in the course of a civil war that ended when ?
RAG:
Lesser battles of the war continued on the periphery for two more years, and minor skirmishes with the remnants of the White forces in the Far East continued well into 1923. The war ended in 1923
Answer: 1923
KG-GraphRAG:
Answer: "Insufficient Information."
Community-GraphRAG:
Alexander Kerensky: *Alexander Kerensky was defeated and destroyed by the Bolsheviks in the course of the Russian Civil War.*
Russian Civil War: *The Russian Civil War was a significant multi-party conflict that took place in the former Russian Empire from November 1917 to October 1922, following the October Revolution.*
Answer: October 1922
Gold Answer: October 1922

Figure 5: Case 1 from Hotpot dataset.

Case 2

Question: Which British first-generation jet-powered medium bomber was used in the South West Pacific theatre of World War II?
RAG:
Answer: "Insufficient Information."
KG-GraphRAG:
No. 12 Squadron → COMBAT_IN → South West Pacific theatre of WWII;
No. 2 Squadron → EQUIPPED_WITH → English Electric Canberra jets;
Answer: English Electric Canberra jets
Community-GraphRAG:
English Electric Canberra: *The English Electric Canberra is a British first-generation jet-powered medium bomber that was manufactured during the 1950s. ...It saw action as a bomber unit in the South West Pacific theatre of World War II and, equipped with English Electric Canberra jets...*
Answer: English Electric Canberra
Gold Answer: English Electric Canberra

Figure 6: Case 2 from Hotpot dataset.

the LLM. The results are presented in Table 13, Table 14, Table 15, Table 16, and Table 17, respectively. For most cases, the integration of RAG and GraphRAG improves performance. However, we observe a performance drop when integrating with Llama 3.1–8B on the MultiHop-RAG dataset. This degradation is primarily attributed to a significant decline on Null queries—those requiring the model to respond with "Insufficient Information." By concatenating the retrieved results from both RAG and GraphRAG, the input length increases considerably, making the 8B model more susceptible to hallucination and the generation of incorrect answers. This vulnerability is more pronounced in the 8B model due to its limited capacity, whereas the 70B model demonstrates greater robustness to longer contexts and handles ambiguous information more conservatively. In contrast, for other query types such as Comparison and

Prompt for Query Classification

System Prompt: Classifying Queries into Fact-Based and Reasoning-Based Categories
You are an AI model tasked with classifying queries into one of two categories based on their complexity and reasoning requirements.
Category Definitions
1. **Fact-Based Queries**
- The answer can be directly retrieved from a knowledge source or requires details.
- The query does not require multi-step reasoning, inference, or cross-referencing multiple sources.
2. **Reasoning-Based Queries**
- The answer cannot be found in a single lookup and requires cross-referencing multiple sources, logical inference, or multi-step reasoning.
Examples
Fact-Based Queries
{{ Fact-Based Queries Examples }}
Reasoning-Based Queries
{{ Reasoning-Based Queries Examples }}

Figure 7: Prompt for Query Classification.

Temporal, the integration strategy yields notable gains on both model sizes.

Table 13: Performance comparison of RAG, GraphRAG, and their integration on NQ and Hotpot datasets

	NQ						Hotpot					
Datasets	Llama 3.1-8B			Llama 3.1-70B			Llama 3.1-8B			Llama 3.1-70B		
Method	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	71.70	63.93	64.78	74.55	67.82	68.18	62.32	60.47	60.04	66.34	63.99	63.88
GraphRAG	69.48	62.54	63.01	71.27	65.46	65.44	64.14	62.08	61.66	67.20	64.89	64.60
Integration	72.81	65.91	66.28	75.67	69.75	69.75	67.21	65.09	64.76	69.22	66.70	66.50

Table 14: The performance of Llama 3.1-8B on MultiHop-RAG dataset

8B	Inference	Comparison	Null	Temporal	Overall
RAG	92.16	57.59	96.01	30.7	67.02
GraphRAG	86.89	60.63	80.07	50.6	69.01
Integration	89.71	64.14	50.17	53.34	68.19

Table 15: The performance of Llama 3.1-70B on MultiHop-RAG dataset

70B	Inference	Comparison	Null	Temporal	Overall
RAG	94.85	56.31	91.36	25.73	65.77
GraphRAG	92.03	60.16	88.7	49.06	71.17
Integration	96.45	73.48	59.47	66.72	77.62

For the query-based summarization task, we observed that the Integration strategy generally performs comparably to RAG, but not significantly better. This is because the evaluation is based on human-written ground-truth summaries, which tend to focus on detailed and faithful representations of the original text. RAG directly retrieves text segments that often match these detailed references more closely, as shown in Figure 4 of our paper. In contrast, GraphRAG primarily retrieves structured information (e.g., entities and relations), which omit finer details needed to align with ground-truth summaries. As a result, while

Table 16: Performance of integrating RAG and GraphRAG with Llama 3.1–8B on the NovelQA dataset.

Integration	character	meaning	plot	relat	settg	span	times	avg
mh	70.83	58.82	63.89	73.03	84.62	60.00	36.90	49.17
sh	62.50	64.29	74.90	62.50	79.38	-	-	70.85
dtl	60.00	43.82	83.93	21.43	72.97	-	-	54.20
avg	63.33	50.19	75.23	60.80	78.23	60.00	36.90	58.36

Integration combines complementary views, the added structured content from GraphRAG does not consistently enhance alignment with detailed ground-truth summaries, leading to comparable or slightly lower scores.

Table 17: Performance of integrating RAG and GraphRAG with Llama 3.1–70B on the NovelQA dataset.

Integration	character	meaning	plot	relat	settg	span	times	avg
mh	77.08	70.59	83.33	77.53	92.31	44.00	37.97	51.99
sh	74.34	74.29	82.43	75.00	87.63	-	-	80.04
dtl	67.14	53.37	92.86	75.00	89.19	-	-	67.21
avg	72.96	60.00	84.29	76.80	88.44	44.00	37.97	65.97

A.7 Query-based Summarization Results with Llama3.1-70B model

In this section, we present the results for Query-based Summarization tasks using the LLaMA 3.1-70B model. The results for single-document summarization are shown in Table 18, while the results for multi-document summarization are provided in Table 19.

Table 18: The performance of query-based single document summarization task using Llama3.1-70B.

Method	SQuALITY						QMSum					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	11.85	14.24	11.00	85.96	85.76	85.67	10.42	10.00	9.53	86.14	85.92	86.02
KG-GraphRAG(Triplets only)	8.53	10.28	7.46	84.13	83.97	83.89	10.62	6.25	7.48	83.20	84.72	83.94
KG-GraphRAG(Triplets+Text)	6.57	10.14	6.00	80.52	82.23	81.07	8.64	7.85	7.29	84.10	84.55	84.31
Community-GraphRAG(Local)	12.54	10.31	9.61	84.50	85.33	84.71	13.69	7.43	9.14	84.09	85.85	84.95
Community-GraphRAG(Global)	8.99	4.78	5.60	81.64	83.64	82.44	10.97	4.40	6.01	81.93	84.67	83.26
Combine	13.59	11.32	10.55	84.88	85.76	85.12	13.16	8.67	9.93	85.18	86.21	85.69

Table 19: The performance of query-based multiple document summarization task using Llama3.1-70B.

Method	ODSum-story						ODSum-meeting					
	ROUGE-2			BERTScore			ROUGE-2			BERTScore		
	P	R	F1	P	R	F1	P	R	F1	P	R	F1
RAG	15.60	9.98	11.09	74.80	81.29	77.89	18.81	6.41	8.97	83.56	85.16	84.34
KG-GraphRAG(Triplets only)	10.08	9.12	8.48	75.71	81.93	78.66	11.52	3.41	4.79	81.19	83.07	82.11
KG-GraphRAG(Triplets+Text)	10.98	16.67	11.42	76.74	81.92	79.21	13.09	6.31	7.70	84.07	84.24	84.14
Community-GraphRAG(Local)	14.20	11.34	11.25	75.44	81.81	78.46	16.17	7.87	9.23	84.17	84.85	84.49
Community-GraphRAG(Global)	10.46	6.30	7.08	74.63	81.24	77.77	10.65	1.99	3.28	79.78	82.53	81.12
Combine	14.76	12.17	11.72	75.39	81.75	78.41	17.57	8.64	10.34	84.51	85.14	84.81

A.8 The LLM-as-a-Judge Prompt

The LLM-as-a-Judge prompt can be found in Figure 8.

LLM-as-a-Judge Prompt

You are an expert evaluator assessing the quality of responses in a query-based summarization task.

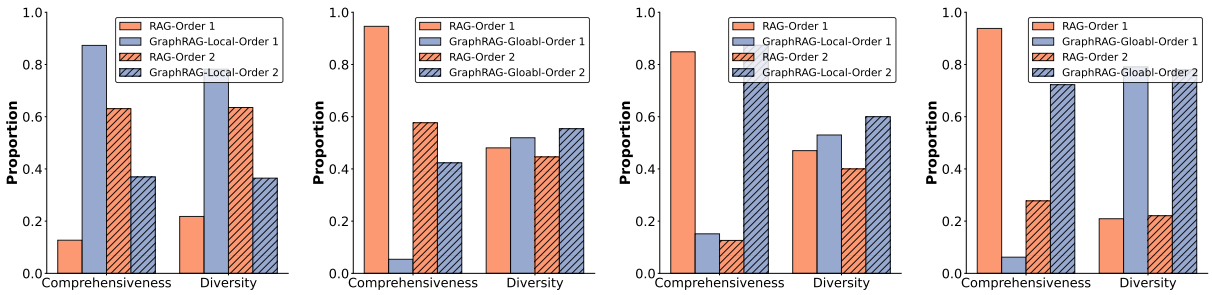
Below is a query, followed by two LLM-generated summarization answers. Your task is to evaluate the best answer based on the given criteria. For each aspect, select the model that performs better.
Query
{{query}}
Answers Section
The Answer of Model 1:
{{answer 1}}
The Answer of Model 2:
{{answer 2}}
Evaluation Criteria Assess each LLM-generated answer independently based on the following two aspects:
1. **Comprehensiveness**
- Does the answer fully address the query and include all relevant information?
- A comprehensive answer should cover all key points, ensuring that no important details are missing.
- It should present a well-rounded view, incorporating relevant context when necessary.
- The level of detail should be sufficient to fully inform the reader without unnecessary omission or excessive brevity.

2. **Global Diversity**
- Does the answer provide a broad and globally inclusive perspective?
- A globally diverse response should avoid narrow or region-specific biases and instead consider multiple viewpoints.
- The response should be accessible and relevant to a wide, international audience rather than assuming familiarity with specific local contexts.

Figure 8: LLM-as-a-Judge Prompt.

A.9 The LLM-as-a-Judge Results on more datasets

In the main section, we present LLM-as-a-Judge results for the OMSum and ODSum-story datasets. Here, we provide additional results on the SQuALITY and ODSum-meeting datasets, as shown in Figure 9.



(a) SQuALITY Local (b) SQuALITY Global (c) ODSum-meeting Local (d) ODSum-meeting Global

Figure 9: Comparison of LLM-as-a-Judge evaluations for RAG and GraphRAG. "Local" refers to the evaluation of RAG vs. GraphRAG-Local, while "Global" refers to RAG vs. GraphRAG-Global. "Order 1" corresponds to the prompt where RAG result is presented before GraphRAG, whereas "Order 2" corresponds to the reversed order.

A.10 Graph Construction with different LLMs

In the main paper, we use GPT-4o-mini to extract entities and relationships for graph construction due to cost considerations. To investigate whether stronger LLMs yield better performance, we also use GPT-4o for graph extraction. Specifically, we evaluate this on the MultiHop-RAG and ODSum-story datasets, representing question answering and summarization tasks, respectively. We focused on Community-GraphRAG (Local) as a representative method (GraphRAG) and evaluated it with both LLaMA3.1-8B and LLaMA3.1-70B for generation.

The results are shown in Table 20, Table 21, Table 22 and Table 23, respectively. The results show that using a stronger LLM (GPT-4o) for graph extraction generally improves the performance of GraphRAG on both question answering and summarization tasks. However, the overall conclusion regarding the relative performance of RAG and GraphRAG remains consistent across different graph construction backbones.

Table 20: Performance of different graph construction methods with Llama 3.1–8B on the MultiHop-RAG dataset.

	Inference	Comparison	NULL	Temporal	Overall
RAG	92.16	57.59	96.01	30.7	67.02
GPT-4o-mini	86.89	60.63	80.07	50.6	69.01
GPT-4o	88.11	62.62	70.43	49.74	68.74

Table 21: Performance of different graph construction methods with Llama 3.1–70B on the MultiHop-RAG dataset.

70B	Inference	Comparison	NULL	Temporal	Overall
RAG	94.85	56.31	91.36	25.73	65.77
GPT-4o-mini	92.03	60.16	88.70	49.06	71.17
GPT-4o	93.63	66.59	81.06	58.49	75.08

Table 22: Performance of different graph construction methods with Llama 3.1–8B on the ODSum-story dataset.

	ROUGE-2			BERTScore		
	P	R	F1	P	R	F1
RAG	15.39	8.44	9.81	83.87	85.74	84.57
GPT-4o-mini	13.84	7.19	8.49	83.19	85.07	83.90
GPT-4o	13.99	7.45	8.64	83.24	85.1	83.94

Table 23: Performance of different graph construction methods with Llama 3.1–8B on the ODSum-story dataset.

	ROUGE-2			BERTScore		
	P	R	F1	P	R	F1
RAG	11.85	14.24	11.09	85.96	85.76	85.67
GPT-4o-mini	12.54	10.31	9.61	84.51	85.33	84.71
GPT-4o	12.08	10.84	9.72	84.66	85.28	84.77

A.11 Computation and Storage Analysis

In this section, we explore the computational and storage trade-offs of RAG, KG-GraphRAG, and Community-GraphRAG. We report construction time, retrieval time, and storage size on two representative datasets: MultiHop-RAG (for question answering) and ODSum-story (for summarization). The results are presented in the Table 24 and Table 25, respectively.

From the reults, we have the following observations:

- **Construction time:** KG-GraphRAG incurs the highest construction time due to the use of LLMs for triplet extraction. However, this process is performed offline.

Table 24: The time and storage analysis on MultiHop-RAG dataset.

Method	Construction Time	Retrieval time	Storage
RAG	135	1724	127MB
KG-GraphRAG	7702	14434	117MB
Community-GraphRAG	5560	1249	165MB

Table 25: The time and storage analysis on ODSum-story dataset

Method	Construction Time	Retrieval time	Storage
RAG	74	350	71MB
KG-GraphRAG	6496	3527	44MB
Community-GraphRAG	2828	282	104MB

- **Storage:** GraphRAG variants generally consume less storage than RAG, with KG-GraphRAG being the most compact due to structured representations.
- **Retrieval time:** KG-GraphRAG shows the highest latency, caused by LLM-based entity expansion during graph traversal. In contrast, Community-GraphRAG achieves the fastest retrieval through direct entity matching, even outperforming RAG.

We also assessed the average retrieved token count, retrieval time, generation time, and performance of our hybrid strategies (Selection and Integration) on the MultiHop-RAG dataset with the Llama3.1-70B model. The results are summarized in Table 26. As shown, the Integration strategy yields the highest performance but introduces the most overhead in terms of tokens and latency due to combining both RAG and GraphRAG content. In contrast, the Selection strategy provides a more balanced trade-off, improving performance over both RAG and GraphRAG individually, while keeping token and time costs significantly lower than GraphRAG.

Table 26: Comparison of retrieved tokens, retrieval time, generation time, and performance using Llama 3.1–70B.

	Average Retrieved Tokens	Retrieval Time	Generation Time	Performance
RAG	3631	1724	3640	65.77
GraphRAG	9770	1249	6272	71.17
Selection	8040	1562	5530	72.3
Integration	13401	2973	9674	77.62

Besides runtime and storage, we also analyze the number of tokens retrieved by Community-GraphRAG and RAG. The results are shown in Table 27.

Table 27: The retrieved number of tokens.

	RAG	Community-GraphRAG
MultiHop-RAG	3631	9770
ODSum-Story	2279	10244

In our experimental setup, RAG retrieves the top-10 text chunks, while Community-GraphRAG (Local) retrieves the top-10 entities and their associated relations. As shown in Table 27, Community-GraphRAG results in significantly more input tokens due to the inclusion of entities, entity descriptions, relations, relation descriptions, and community summaries.

To ensure a fair comparison, we conducted an additional experiment in which we increased the number of retrieved text chunks for RAG to match the total number of input tokens retrieved by Community-GraphRAG. The results are shown in Table 28, Table 29, Table 30 and Table 31. While increasing RAG's input size does lead to slight performance gains, our main conclusions remain unchanged: RAG

performs better on inference-style queries and summarization tasks, where detailed information is directly retrievable. In contrast, GraphRAG performs better on complex queries such as Comparison and Temporal types in MultiHop-RAG, which require multi-hop reasoning and aggregation.

Table 28: Performance comparison of RAG, token-matched RAG, and GraphRAG using Llama 3.1–8B on MultiHop-RAG dataset.

	Inference	Comparison	NULL	Temporal	Overall
RAG	92.16	57.59	96.01	30.7	67.02
RAG_Same Token	95.34	59.81	89.04	36.71	69.33
GraphRAG	86.89	60.63	80.07	50.6	69.01

Table 29: Performance comparison of RAG, token-matched RAG, and GraphRAG using Llama 3.1–70B on MultiHop-RAG dataset.

70B	Inference	Comparison	NULL	Temporal	Overall
RAG	94.85	56.31	91.36	25.73	65.77
RAG_Same Token	95.96	59.58	88.7	43.74	71.01
GraphRAG	92.03	60.16	88.7	49.06	71.17

Table 30: Performance comparison of RAG, token-matched RAG, and GraphRAG using Llama 3.1–8B on ODSum-Story dataset.

8B	ROUGE-2			BERTScore		
	P	R	F1	P	R	F1
RAG	15.39	8.44	9.81	83.87	85.74	84.57
RAG_Same Token	14.16	10.02	10.16	84.34	85.74	84.82
GraphRAG	13.84	7.19	8.49	83.19	85.07	83.9

Table 31: Performance comparison of RAG, token-matched RAG, and GraphRAG using Llama 3.1–70B on ODSum-Story dataset.

	ROUGE-2			BERTScore		
	P	R	F1	P	R	F1
RAG	11.85	14.24	11.09	85.96	85.76	85.67
RAG_Same Token	12.82	14.07	11.34	85.86	86	85.73
GraphRAG	12.54	10.31	9.61	84.51	85.33	84.71