Structured Knowledge Representation through Contextual Pages for Retrieval-Augmented Generation

Anonymous ACL submission

Abstract

Retrieval-Augmented Generation (RAG) enhances Large Language Models (LLMs) by incorporating external knowledge. Recently, some works have incorporated iterative knowledge accumulation processes into RAG models to progressively accumulate and refine external knowledge. However, these methods exhibit a phenomenon of sub-query intention convergence during the iterative question decomposition process, which limits the acquisition of comprehensive and diverse knowledge for constructing more comprehensive knowledge representations. To address this, we propose PAGER, a reasoning-augmented autonomous knowledge representation framework for RAG. PAGER first prompts an LLM to construct a structured reasoning outline for the given question, which consists of multiple slots representing a distinct knowledge aspect. Then, PAGER iteratively retrieves and refines relevant documents to fill each slot, ultimately constructing a coherent page that serves as contextual input for guiding answer generation. Experiments on multiple datasets and backbone models show that PAGER consistently outperforms all RAG baselines. Further analyses demonstrate that PAGER constructs higher-quality and information-dense knowledge representations, better mitigates knowledge conflicts, and enables LLMs to leverage external knowledge more effectively. All codes and datasets will be available via GitHub.

1 Introduction

Retrieval-Augmented Generation (RAG) models enhance the performance of Large Language Models (LLMs) by retrieving relevant documents and using them as context inputs (Guu et al., 2020; Lewis et al., 2020). Recent studies have begun to focus on refining retrieved knowledge to enhance RAG models (Wu et al., 2025; Xu et al., 2023c; Zhu et al., 2025), which typically incorporate specialized modules to refine retrieved documents into

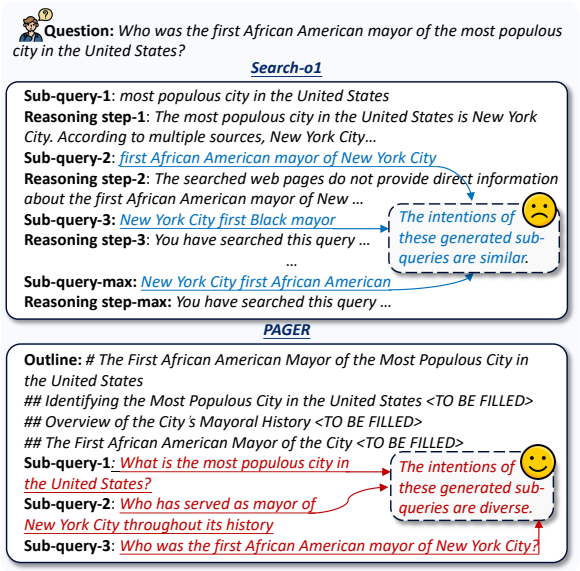


Figure 1: The Phenomenon of Sub-queries Intention Convergence. Compared to Search-o1, which generates semantically redundant sub-queries until the maximum number of iterations, PAGER leverages the reasoning ability of LLMs to generate a structured outline where each slot constrains the model to query a specific type of missing knowledge, thereby generating more diverse sub-queries.

either unstructured summaries (Vig et al., 2022) or structured knowledge (Li et al., 2025b), enabling LLMs to utilize the retrieved knowledge more effectively. However, these methods primarily focus on tailoring the representation of retrieved knowledge while failing to fully leverage the structure of knowledge representations and the retriever to actively acquire and complete missing knowledge, which limits their application to complex questions (Guo et al., 2025; Jiang et al., 2025a).

To achieve more effective knowledge acquisition and utilization, some studies have begun incorporating iterative knowledge accumulation processes into RAG models (Trivedi et al., 2023; Jin et al., 2025a). These methods design iterative knowledge

acquisition mechanisms that leverage the strong reasoning capabilities of LLMs to progressively obtain and refine new knowledge, thereby incorporating more information to construct more comprehensive knowledge representations (Wang et al., 2025a; Li et al., 2025a). However, these methods exhibit a phenomenon of subquery intention convergence during the iterative question decomposition process. As shown in Figure 1, as the reasoning process progresses, Search-o1 (Li et al., 2025a) tends to generate sub-queries or outputs with similar intentions (Rezaei and Dieng, 2025), leading to excessive retrieval (Jiang et al., 2025b), which limits its ability to acquire more comprehensive and diverse knowledge to construct a coherent knowledge representation. To overcome this challenge, models need to leverage their inherent reasoning ability to generate reasoning trajectories for the given query (Wang et al., 2024), which expose the required aspects and topics of knowledge, thereby constraining the model to query specific missing knowledge to generate diverse sub-queries.

In this paper, we introduce PAGER, a reasoning-augmented autonomous knowledge representation framework that constructs structured reasoning outline for RAG modeling, enabling LLMs to leverage their reasoning capability to more effectively acquire more diverse knowledge to build page representations. PAGER first prompts the LLM to draw on its parametric knowledge to generate a structured reasoning trajectory as a page outline for the target question. The outline consists of multiple blank slots, each representing a distinct aspect of the potentially relevant knowledge needed to answer the question, requiring knowledge to complete. Then PAGER employs an iterative knowledge completion mechanism to iteratively retrieve supporting documents for each blank slot, refine them into concise knowledge evidence, and fill the corresponding slot in the page. This iterative process continues until all slots in the page are filled with the corresponding knowledge evidence. Finally, PAGER uses this page as context knowledge to guide the LLM to answer the given question.

Experimental results demonstrate that PAGER consistently outperforms all baseline methods on knowledge-intensive tasks of varying scenarios and different backbone models, demonstrating its effectiveness. Further analysis shows that the cognitive architecture designed by PAGER can more effectively guide LLMs to acquire and organize knowledge, yielding coherent and comprehensive knowledge representations that support question answering. Furthermore, compared to other knowledge representations, the structured knowledge pages exhibit richer information content and superior quality, demonstrating the effectiveness of the knowledge representations constructed by PAGER. Meanwhile, by leveraging the reasoning capability of LLMs to organize external knowledge into structured pages, PAGER effectively mitigates knowledge conflicts within LLMs and enables them to utilize knowledge more effectively.

2 Related Work

Large language models (LLMs) (Yang et al., 2025; Dubey et al., 2024) have demonstrated strong capabilities across a wide range of tasks (Trivedi et al., 2023; He et al., 2021). However, LLMs typically suffer from hallucination, which can lead to incorrect responses (Jiang et al., 2023; Xu et al., 2023b). To mitigate this issue, existing studies employ RAG models, which retrieve relevant documents for a given question and incorporate them as input context, enabling LLMs to access external knowledge and generate accurate answers (Lewis et al., 2020; Guu et al., 2020). However, the conflict between retrieved knowledge and parametric memory hinders the LLM's ability to reliably identify critical facts from retrieved documents, limiting the effectiveness of RAG models (Huo et al., 2025).

To address these challenges, some studies have focused on refining knowledge to capture crucial evidence from retrieved documents (Wu et al., 2025). Some studies use query-focused summarization methods (Xu et al., 2023c) to condense retrieved documents into shorter forms, thereby reducing noise and enhancing relevance. Furthermore, several studies have begun exploring refining the retrieved documents into structured knowledge representation, such as graphs (Zhu et al., 2025) or tables (Li et al., 2025b), thereby better capturing knowledge from different documents. However, despite the availability of retrieval tools, these methods still fail to fully leverage them to actively acquire missing information and complete the knowledge representation.

Recently, some studies have shifted toward acquiring and accumulating additional knowledge to enhance the process of refined knowledge representation (Trivedi et al., 2023). These methods iteratively generate sub-queries to existing knowledge gaps, retrieve relevant documents, and apply differ-

ent knowledge refinement strategies to construct diverse knowledge representations (Wang et al., 2024, 2025a). For example, Wang et al. (2025a) refine knowledge into note-based representations, and Li et al. (2025a) adopt a reasoning-in-document mechanism that integrates knowledge into the reasoning trajectory. However, these methods exhibit a phenomenon of subquery intention convergence during the iterative subquery generation process, making it difficult for the model to acquire diverse knowledge for constructing a comprehensive knowledge representation (Rezaei and Dieng, 2025). To overcome this limitation, PAGER leverages the inherent reasoning capability of the LLM to construct a structured reasoning outline, thereby better guiding and constraining the knowledge acquisition process, and employs iterative knowledge completion to build a structured page representation for answering the given question.

3 Methodology

In this section, we introduce PAGER, a reasoning-augmented autonomous knowledge representation framework. We first describe the preliminaries of RAG models enhanced with structured knowledge representations (Sec. 3.1) and then describe the construction of coherent and comprehensive knowledge representations via autonomous page construction (Sec. 3.2).

3.1 Preliminaries: Enhancing RAG Models with Structured Knowledge

Recent RAG approaches incorporate structured knowledge representations to refine retrieved information (Li et al., 2025b). Different from them, PAGER aims to guide an LLM to iteratively retrieve relevant documents and complete knowledge representations by autonomously interacting with retrieval tools, thereby enabling more accurate and reliable query answering.

Knowledge Refinement with Structured Representations. Given a query q, existing methods (Li et al., 2025b) first retrieve the top-k relevant documents:

$$D = \text{Search}(q, k), \tag{1}$$

where $D = \{d_1, \ldots, d_k\}$. Subsequently, the LLM is prompted to refine the retrieved documents into a query-conditioned structured knowledge representation result O. The refined knowledge O can take various forms, such as tables, graphs, or other structured abstractions. The structured knowledge O is then provided as context input to the LLM $\mathcal{M}$ for generating the answer y:

$$y = \mathcal{M}\big(\text{Instruct}_{\text{QA}}(O, q)\big), \tag{2}$$

where $\text{Instruct}_{\text{QA}}$ denotes the instruction template that guides the LLM to generate an answer based on the structured knowledge. Despite their effectiveness, these approaches primarily treat structured knowledge as a post-retrieval refinement artifact. Even though modern LLMs possess strong reasoning capabilities, existing approaches fail to fully leverage such capabilities to explore the potential of structured knowledge representations for identifying missing information, guiding knowledge acquisition, and supporting knowledge completion.

Reasoning-augmented Knowledge Completion. In contrast to prior methods that rely on static structures for knowledge refinement, we propose PAGER, which introduces a reasoning-augmented *page* structure to facilitate knowledge acquisition and completion for the question, resulting in a structured page p:

$$p = \mathcal{F}_{\text{page}}\big(q, \text{Search}(\cdot), \mathcal{M}\big), \tag{3}$$

where $\mathcal{F}_{\text{page}}$ denotes the page construction function. This function leverages the reasoning capability of LLMs to generate a structured reasoning trajectory as the page outline, which includes the potential aspects of knowledge required to answer the question. Subsequently, the function autonomously accumulates and organizes knowledge through iterative interactions with retrieval tools to complete the outline, as detailed in Sec. 3.2. The LLM then performs reasoning over the resulting structured page p to derive the final answer y:

$$y = \mathcal{M}\big(\text{Instruct}_{\text{QA}}(p, q)\big). \tag{4}$$

3.2 Knowledge Representation via Structured Page Construction

In this subsection, we provide a detailed description of the PAGER. We first introduce the reasoning-guided page initialization mechanism in PAGER, and then describe how PAGER iteratively completes knowledge to construct a structured page.

Reasoning-guided Page Initialization. Given a query q, we initialize the page's outline solely based on the intrinsic reasoning capabilities of the LLM.

Specifically, we design an instruction template $\text{Instruct}_{\text{outline}}$ to prompt the LLM to analyze the query q and generate a coherent reasoning trace

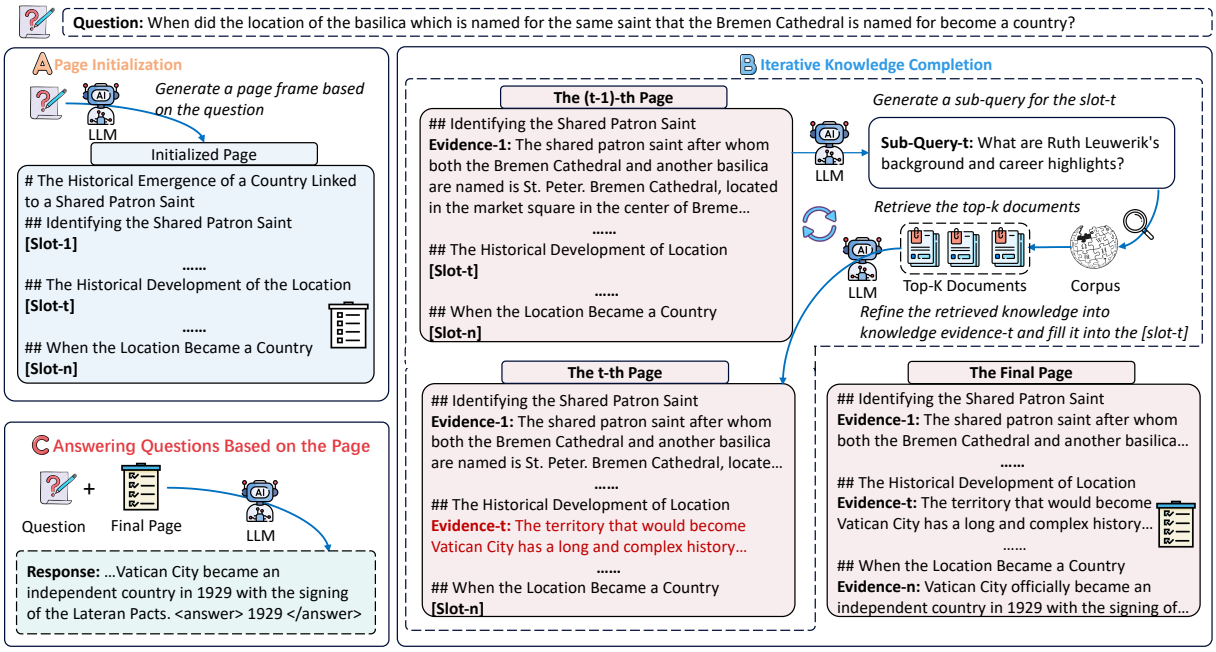


Figure 2: The Illustration of Our PAGER Model.

r, which captures the LLM's internal analytical process and semantic understanding of the query q. Conditioned on this reasoning process, the model then generates a structured reasoning, which serves as the initial page p_0:

$$r, p_0 = \mathcal{M}(\text{Instruct}_{\text{outline}}(q)), \tag{5}$$

where the initial page p_0 is formulated as a structured reasoning outline comprising n explicitly defined blank slots, which are reserved for subsequent knowledge completion:

$$p_0 = \text{Outline}(\texttt{[b]}_1, \ldots, \texttt{[b]}_n), \tag{6}$$

where $\texttt{[b]}_i$ denotes the i-th placeholder corresponding to a specific knowledge component required to answer the query. By leveraging the reasoning capability of the LLMs, PAGER establishes a structured knowledge outline for the query, decomposing it into n thematically organized knowledge slots that specify the potential supporting information. However, such a reasoning-driven outline remains abstract and lacks concrete supporting evidence (Wang et al., 2024). This motivates subsequent knowledge retrieval and accumulation to progressively fill these blank slots, further completing and supplementing the knowledge outline.

Iterative Knowledge Completion. PAGER then performs an iterative knowledge refinement process to fill the blank slots $\texttt{[b]}_{1:n}$ in p_0.

At each iteration step t ($1 \leq t \leq n$), the $(t-1)$-th page is represented as:

$$p_{t-1} = \text{Outline}(s_1, \ldots, s_{t-1}, \texttt{[b]}_t, \ldots, \texttt{[b]}_n). \tag{7}$$

PAGER obtains the page p_t by updating the $(t-1)$-th page p_{t-1} through filling the t-th slot $\texttt{[b]}_t$:

$$s_t \xrightarrow{\text{fill}} \texttt{[b]}_t, \tag{8}$$

where s_t is a refined knowledge evidence used to fill the blank slot $\texttt{[b]}_t$. Through this progressive iterative mechanism, external knowledge is gradually refined and incorporated into the knowledge pages until all n slots are filled with supporting evidence, yielding the final structured page p_n.

To gather knowledge evidence s_t for the slot $\texttt{[b]}_t$, we first prompt the LLM to generate a sub-query q_t tailored to gather necessary knowledge to fill the t-th slot $\texttt{[b]}_t$ in p_{t-1}:

$$q_t = \mathcal{M}(\text{Instruct}_{\text{query}}(p_{t-1}, q)), \tag{9}$$

where $\text{Instruct}_{\text{query}}$ is an instruction template designed to guide the LLM to focus on the blank slot $\texttt{[b]}_t$ and produce a sub-query q_t. It is important to emphasize that the content of the sub-query are not entirely equivalent to the themes of the slots in the outline. The generation of the sub-query is dynamic and iterative, referencing the current page state, and is not strictly constrained by the slots[1]. Next, the retriever model is employed to search k documents D_t based on the generated query q_t:

$$D_t = \text{Search}(q_t, k). \tag{10}$$

[1]A more detailed description is provided in Appendix A.3.

Finally, the LLM is prompted using $\text{Instruct}_{\text{fill}}$ to generate the knowledge evidence s_t based on the retrieved documents D_t:

$$s_t = \mathcal{M}(\text{Instruct}_{\text{fill}}(q, p_{t-1}, D_t, q_t)). \quad (11)$$

4 Experimental Methodology

In this section, we describe the datasets, evaluation metrics, and baselines. The experimental implementation details are provided in Appendix A.2.

Dataset. Following previous work (Li et al., 2025a; Song et al., 2025), we evaluate our method on both multi-hop and single-hop QA benchmarks. Specifically, we select HotpotQA (Yang et al., 2018), 2WikiMultiHopQA (Ho et al., 2020), MuSiQue (Trivedi et al., 2022), and Bamboogle (Press et al., 2023) for multi-hop tasks, while using NQ (Kwiatkowski et al., 2019) and AmbigQA (Min et al., 2020) for single-hop tasks. For evaluation, we randomly sample 2,000 instances from the dev set of each dataset, except for Bamboogle (Press et al., 2023), where we utilize the test set (125 instances) due to its limited size.

Evaluation Metrics. We follow existing work (Sun et al., 2025; Song et al., 2025) to utilize Cover Exact Match as the evaluation metric.

Baselines. In our experiments, we compare PAGER with multiple baseline models, including a Vanilla LLM, one-pass retrieval RAG models, iterative retrieval RAG models, and iterative knowledge representation construction RAG models.

For the Vanilla LLM, we directly feed the query to the LLM and ask it to generate the answer. For one-pass retrieval RAG models, we adopt Vanilla RAG, StructRAG (Li et al., 2025b) and ReWOO (2023a). Vanilla RAG utilizes retrieved documents as contextual input to assist the LLM in answering the question. StructRAG designs a router to refine documents into structured knowledge representations as input context. ReWOO generates all sub-queries for the given question in a single pass and executes them in parallel to retrieve external knowledge for reasoning. For iterative retrieval RAG models, we employ Iter-RetGen (Shao et al., 2023) and IRCoT (Trivedi et al., 2023) to accumulate knowledge for assisting the LLM. These methods interleave retrieval with the generation process, utilizing intermediate generated content to guide subsequent retrieval and directly leveraging the retrieved documents to facilitate the generation process. Besides, we adopt RAT (Wang et al., 2024), Search-o1 (Li et al., 2025a), and DeepNote (Wang et al., 2025a) as iterative knowledge representation construction RAG models. Specifically, RAT directly prompts the LLM to generate CoT-style knowledge representations and iteratively retrieves external knowledge to refine each reasoning step. Search-o1 performs adaptive retrieval and applies a Reason-in-Document mechanism to refine the retrieved documents, integrating them into the CoT-style representation. DeepNote compresses retrieved knowledge into note-based representations and iteratively acquires additional information to update these notes.

5 Experimental Results

In this section, we first evaluate the performance of PAGER across different models and datasets. Subsequently, we conduct ablation studies to analyze the effectiveness of different functional components in PAGER. Then, we investigate the effectiveness of the pages in knowledge representation. Finally, we explore the impact of different representations on knowledge utilization in LLMs.

5.1 Overall Performance

As shown in Table 1, we compare the overall performance of PAGER with various baseline methods across a range of knowledge-intensive tasks.

Overall, PAGER demonstrates its effectiveness by outperforming all baseline models, achieving improvements exceeding 2%. Notably, PAGER consistently shows improvements across various tasks and backbone LLMs, underscoring its robust generalization ability. When compared to StructRAG, PAGER delivers an average performance boost of over 5%, indicating that the page format serves as an effective knowledge representation mechanism, enabling autonomous interaction with external knowledge to build more comprehensive knowledge structures. Furthermore, in comparison to iterative retrieval-based methods like IRCoT and Iter-RetGen, PAGER achieves an improvement of over 9%, emphasizing its role in more effectively refining and organizing retrieved evidence. In addition, PAGER outperforms DeepNote and Search-o1, suggesting that the reasoning-augmented structured page enables the model to generate more effective knowledge representations, thus providing stronger support for LLMs in answering questions.

5.2 Ablation Study

In this subsection, we conduct ablation studies to evaluate the effectiveness of different components in PAGER.

Methods	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
Qwen3-32B							
Vanilla LLM	28.6	31.8	8.2	44.0	36.2	32.9	30.3
Vanilla RAG	42.9	36.5	13.5	52.0	54.6	54.8	42.4
StructRAG (2025b)	42.5	31.5	12.8	44.8	55.1	54.5	40.2
IRCoT (2023)	45.1	45.5	14.7	32.0	52.2	51.8	40.2
Iter-RetGen (2023)	43.2	40.2	14.5	37.6	**56.5**	55.4	41.2
RAT (2024)	43.7	45.0	16.1	55.2	53.2	55.5	44.8
ReWOO (2023a)	43.6	50.7	14.1	51.2	54.4	52.1	44.4
Search-o1 (2025a)	47.6	47.0	22.9	33.6	49.2	51.5	42.0
DeepNote (2025a)	48.4	47.2	17.2	39.2	55.6	55.9	43.9
PAGER	**50.6**	**57.4**	**23.0**	**62.4**	**56.5**	**56.4**	**51.1**
Llama3.1-70B-Instruct							
Vanilla LLM	37.7	41.5	14.1	57.6	50.3	48.8	41.7
Vanilla RAG	48.2	41.9	19.1	56.8	55.7	57.0	46.5
StructRAG (2025b)	49.6	44.1	19.4	57.6	**57.4**	58.2	47.7
IRCoT (2023)	35.2	37.0	6.2	11.2	49.9	50.3	31.6
Iter-RetGen (2023)	41.1	34.5	11.9	32.8	53.0	52.3	37.6
RAT (2024)	48.9	40.2	20.8	58.4	53.6	56.4	46.2
ReWOO (2023a)	45.2	44.7	17.0	50.4	54.3	54.0	44.3
Search-o1 (2025a)	50.2	**55.4**	22.9	58.4	51.6	53.8	48.3
DeepNote (2025a)	51.7	48.9	20.8	58.4	56.6	58.4	49.1
PAGER	**52.4**	54.9	**24.3**	**62.4**	56.4	**60.0**	**51.7**

Table 1: Overall Performance of Different RAG Models. The **best** and second best results are highlighted.

Methods	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
Qwen3-32B							
PAGER (Parallel Filling)	45.9	43.8	18.8	59.2	56.4	**57.0**	46.9
PAGER	**50.6**	**57.4**	**23.0**	**62.4**	**56.5**	56.4	**51.1**
w/o IterRetrieval	44.8	42.2	16.9	52.0	54.6	55.1	44.3
w/o Initilization	46.2	45.2	15.9	48.0	55.2	55.9	44.4
Llama3.1-70B-Instruct							
PAGER (Parallel Filling)	47.4	43.4	18.6	58.4	**57.2**	59.5	47.4
PAGER	**52.4**	**54.9**	**24.3**	**62.4**	56.4	**60.0**	**51.6**
w/o IterRetrieval	47.6	41.6	18.1	56.0	56.3	58.1	46.3
w/o Initilization	51.1	50.5	21.4	60.0	55.9	57.9	49.5

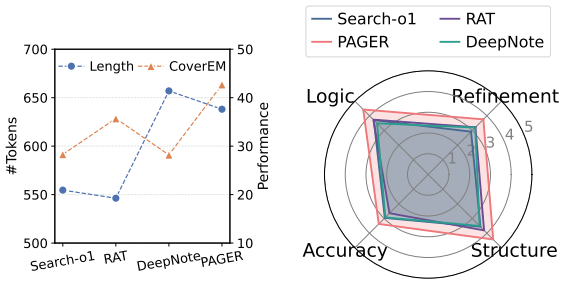
Table 2: Ablation Study. The **best** and second best results are highlighted.

In the experiments, we compare PAGER with three ablated models: PAGER (Parallel Filling) simultaneously generates sub-queries for all missing slots in the initial page, conducts parallel retrieval and then refines these retrieved documents to fill into the corresponding slots; PAGER (w/o IterRetrieval) conducts a single-pass retrieval based on the given query and filling the intial pages based on these retrieved docuemtns; PAGER (w/o Initialization) iteratively refines the retrieved documents into concise summaries, concatenating them until the aggregated summaries are sufficient to answer the question. This variant removes the page initialization stage, which typically generates the outline based on the reasoning ability of LLMs.

As shown in Table 2, PAGER consistently outperforms PAGER (Parallel Filling), demonstrating the effectiveness of the iterative knowledge completion mechanism in PAGER. Unlike parallel retrieval, PAGER generates sub-queries conditioned on the page state at the previous step, which enables more tailored sub-queries for retrieving necessary information and helps avoid homogeneous content to fill in different page slots. Furthermore, compared to PAGER (w/o IterRetrieval), PAGER exhibits consistent performance gains across different datasets and backbone models, indicating that iterative retrieval can incorporate more essential information to better answer the given query. Finally, compared with PAGER (w/o Initialization), PAGER achieves further improvements, highlighting the critical role of the outline generated by leveraging the reasoning capability of LLMs. This outline guides PAGER to effectively acquire and complete the required knowledge within a page.

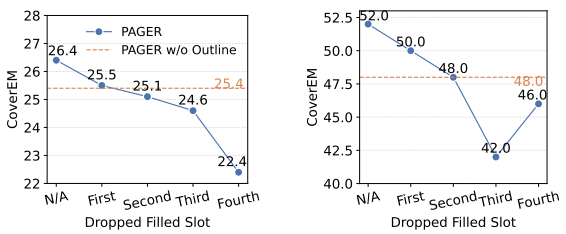
5.3 The Effectiveness of Constructed Pages in Knowledge Representation

In this section, we investigate the effectiveness of PAGER in knowledge representation by analyzing its constructed pages. Specifically, we examine both the quality of the constructed pages produced



(a) Representation Length. (b) GLM Score.

Figure 3: The Quality of Knowledge Representations Constructed by Different Methods.



(a) MuSiQue. (b) Bamboogle.

Figure 4: Slot Ablation Studies on the Constructed Page. "N/A" denotes the complete page with no filled slots removed. "First", "Second", "Third", and "Fourth" denote the variants in which the First, Second, Third, and Fourth filled slots are removed, respectively. PAGER (w/o Outline) denotes a variant where the cognitive outline is removed from the completed page.

by PAGER and how these pages facilitate knowledge utilization by LLMs. In this experiment, we adopt Qwen3-32B as the backbone model and conduct evaluations on the MuSiQue and Bamboogle.

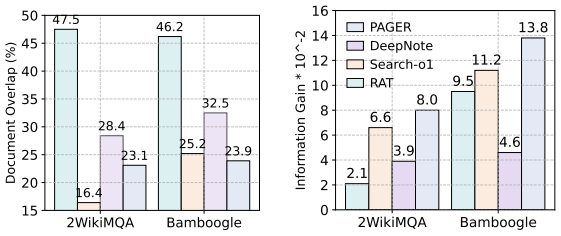
The Quality of PAGER in Representing Knowledge. Figure 3 presents the length statistics and quality of the knowledge representations.

As shown in Figure 3(a), we compute the average token length of knowledge representations generated by different methods to analyze the trade-off between the length and QA performance. Compared with RAT and Search-o1, PAGER achieves superior performance with longer knowledge representations, indicating that PAGER enhances QA performance by incorporating richer information to form more comprehensive knowledge representations. Compared with DeepNote, PAGER attains significantly better performance while reducing the length of the knowledge representation. This suggests that PAGER exhibits higher knowledge density than DeepNote, enabling it to deliver more effective information within the constructed page.

We further evaluate the quality of the knowledge representations generated by different models. As shown in Figure 3(b), we employ a strong closed-source LLM, GLM-4.5, as the evaluator. Using the prompt templates provided in Appendix A.10, we assess the knowledge representations along four dimensions: accuracy, logicality, structure, and degree of knowledge refinement, with each dimension rated on a scale from 0 to 5. The evaluation results demonstrate that PAGER consistently outperforms other models across all dimensions, with particularly notable advantages in structure and logical consistency. These findings further validate the effectiveness of PAGER in reasoning-augmented knowledge representation, which enables the model to acquire the necessary knowledge more logically guided by the structured reasoning outline.

Effectiveness of Completed Knowledge in Different Slots of the Page. As shown in Figure 4, we further analyze the effectiveness of the knowledge filled in different slots of the page. We collect pages containing four slots as seed pages (As shown in Appendix A.8, the pages constructed by the Qwen3-32B predominantly feature 4 slots). Then, we remove the first, second, third, and fourth filled slots to construct incomplete pages, respectively. Finally, we feed these four distinct incomplete pages into the model to evaluate the performance.

Overall, compared with the completed page PAGER (N/A), removing any single filled slots from the page leads to performance degradation, indicating that all filled knowledge is necessary to support LLMs in answering the query. As the removed filled slot shifts from the first slot to the fourth slot, the model performance degrades more substantially, suggesting that knowledge filled in later slots is more critical for question answering. One possible reason is that our iterative completion method tends to acquire increasingly necessary knowledge in later slots, which aligns with the reasoning process of LLMs, where later reasoning steps often involve deeper inference to answer the query. Furthermore, compared with PAGER (N/A), PAGER (w/o Outline) also exhibits a performance decline. This observation further indicates that the structured reasoning outline plays a critical role in guiding the knowledge construction process, thereby validating the effectiveness of our page initialization module.



(a) Document Overlap. (b) Information Gain.

Figure 5: Effects of Different Knowledge Representations on Retrieval and Generation Modules of RAG.

Methods	2WikiMQA	Bamboogle	HotpotQA
Knowledge Conflict			
Vanilla LLM	100.0	100.0	100.0
Vanilla RAG	61.1	90.9	82.2
DeepNote	64.5	58.2	82.2
RAT	72.8	**92.7**	84.9
Search-o1	56.3	52.7	82.6
PAGER	**73.4**	83.6	**87.6**
Knowledge Utilization			
Vanilla LLM	0.0	0.0	0.0
Vanilla RAG	25.1	21.4	27.2
DeepNote	39.2	24.3	34.9
RAT	32.0	25.7	27.2
Search-o1	42.7	18.6	33.5
PAGER	**49.9**	**45.7**	**35.8**

Table 3: Performance of Different RAG Models under Different Testing Scenarios.

5.4 The Impact of Different Representations on Knowledge Utilization in LLMs

In this section, we investigate how different knowledge representations affect knowledge utilization in LLMs. We adopt Qwen3-32B as the backbone model for all experiments.

As shown in Figure 5, we evaluate the effectiveness of constructed knowledge representations across different RAG models. First, we analyze the document overlap between successive retrieval steps using the Jaccard similarity. As illustrated in Figure 5(a), the results show that PAGER exhibits substantially lower document overlap than DeepNote and RAT. This suggests that the page-based representation can efficiently reduce the generation of duplicate subqueries and the retrieval of redundant content, encouraging the model to incorporate more diverse knowledge instead of repeatedly retrieving similar information. Following prior work (Wang et al., 2025b), we further compute the information gain of different knowledge representations, as reported in Figure 5(b). Information gain quantifies the contribution of a knowledge representation to correct answer generation, with details provided in Appendix A.4. The results demonstrate that the pages constructed by PAGER achieve higher knowledge information gain than other methods. This indicates that the knowledge encoded in structured page representations can better guide LLMs toward generating accurate answers.

Next, we evaluate the impact of different knowledge representations on knowledge conflicts and knowledge utilization in LLMs. As shown in Table 3, we design two evaluation scenarios: knowledge conflict and knowledge utilization. For the knowledge conflict scenario, we select samples from the evaluation dataset where the LLM can generate correct answers solely based on its parametric knowledge, aiming to assess the denoising capability of RAG systems. For the knowledge utilization scenario, we construct the evaluation set by selecting samples where the LLM must rely on external knowledge to generate the answer. The evaluation results show that both PAGER and RAT perform more effectively in the knowledge conflict scenario, indicating that incorporating the raw reasoning of LLMs to organize retrieved knowledge can alleviate conflicts between internal and external knowledge. In contrast, DeepNote and Search-o1 outperform RAT in the knowledge utilization setting, suggesting that incorporating more retrieved knowledge provides greater potential for correcting factual errors in memorized knowledge. Notably, PAGER achieves the best performance in the knowledge utilization and knowledge conflict scenarios. These results suggest that the page representation, by leveraging reasoning-guided knowledge acquisition and structured knowledge representation, offers a more tailored balance between mitigating knowledge conflicts and enhancing knowledge utilization.

6 Conclusion

This paper presents PAGER, a reasoning-augmented autonomous knowledge representation framework for RAG. By constructing a structured outline and iteratively filling it with retrieved evidence, PAGER organizes external knowledge into the structed page representation that better supports LLM to answer the questions. Experimental results show that PAGER consistently outperforms baselines across multiple tasks and backbone models.

Limitations

Although PAGER achieves superior performance across multiple datasets, the page construction process introduces additional latency. Specifically, to ensure the logical coherence and completeness of the constructed pages, PAGER employs an iterative slot-filling mechanism. This iterative process inevitably incurs extra computational overhead, leading to increased inference latency. Moreover, we also explore a variant of PAGER with parallel filling to mitigate this issue. However, experimental results indicate that the iterative design is still necessary to maintain the effectiveness of PAGER when answering multi-hop QA queries. Therefore, the trade-off between effectiveness and efficiency remains a critical challenge for fully deploying PAGER in real-world QA scenarios.

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A Appendix

A.1 License

We show the licenses of the datasets that we use. All of these datasets are allowed for academic use under their respective licenses and agreements: MuSiQue and HotpotQA (CC-BY-4.0 License); 2WikiMQA (Apache 2.0 License); Bamboogle (MIT License); NQ and AmbigQA (CC BY-SA 3.0 License).

A.2 More Implementation Details

In our experiments, we employ Qwen3-32B (Yang et al., 2025), and Llama-3.1-70B-Instruct (Dubey et al., 2024) as backbone models. We follow FlashRAG (Jin et al., 2025b) to use Wikipedia as the retrieval corpus and adopt Qwen3-Embedding-0.6B (Zhang et al., 2025) as the embedding model and employ FAISS (Johnson et al., 2019) to build indexes for retrieval. We utilize FlashRAG (Jin et al., 2025b) to reproduce the results of IRCoT and Iter-RetGen on the experimental datasets. We further employ the vLLM inference framework (Kwon et al., 2023) to accelerate inference across all models. For RAT, Search-o1, StructRAG, and DeepNote, we reproduce their results using the official GitHub code provided. During inference, we use vLLM to load model checkpoints and perform offline batched generation, while setting unified hyperparameters: temperature = 0.7, top-p = 0.8, top-k = 20, and random seed = 66. During retrieval, the top-5 ranked documents are retained for all RAG models.

A.3 The Role and Characteristics of the Page Outline in the Page Construction Process

The page outline initialized by PAGER consists of multiple slots, where each slot represents a specific aspect of potentially relevant knowledge and background information required to answer the question. Guided by this outline, PAGER can pose sub-queries from different aspects during the subsequent iterative generation of sub-queries, thereby retrieving more diverse knowledge. It is worth noting that, although the generation of the t-th sub-query is guided by the t-th blank slot in the current page, the semantics of the generated sub-query are not equivalent to the topic of that slot. This is because each sub-query is generated iteratively and dynamically by the model with reference to both the evidence already filled in the current page and the overall page structure. In this process, the slots provide potential dimensions for sub-query generation, rather than strictly limiting or constraining the generation process itself. Therefore, during page construction, PAGER does not adjust the page outline, but instead maintains a static outline structure. This not only improves the efficiency of page construction but also preserves the logical consistency of the page outline. In the following sections, we will further analyze the difference between the slots in the page outline and the generated sub-queries, as well as why a fixed outline structure is chosen without dynamic adjustments, by presenting examples and experiments.

Case #1

Question: What league does the team that uses Dick's Sporting Goods Park play for?

Page Frame:
The League of the Team at Dick's Sporting Goods Park
Identifying the Team at Dick's Sporting Goods Park
<TO BE FILLED>
Determining the League the Team Belongs To
<TO BE FILLED>
Understanding the Context of the League
<TO BE FILLED>

Generate Sub-query:
1. Which team uses Dick's Sporting Goods Park as its home venue?
2. What league do the Colorado Rapids play in?
3. What is the context or significance of Major League Soccer (MLS) in relation to the Colorado Rapids?

Case #2

Question: What rocket was the first spacecraft that ever approached Uranus launched on?

Page Frame:
The Rocket Behind the First Spacecraft to Approach Uranus
Introduction to the Spacecraft That Approached Uranus
<TO BE FILLED>
The Rocket Used to Launch the Spacecraft
<TO BE FILLED>
Historical Context of the Mission
<TO BE FILLED>
Journey and Observations at Uranus
<TO BE FILLED>

Generate Sub-query:
1. What was the name of the first spacecraft to approach Uranus?
2. What rocket was used to launch NASA's *Voyager 2* spacecraft?
3. What was the historical context surrounding the launch and mission of NASA's *Voyager 2*?
4. What is the scientific impact and legacy of NASA's *Voyager 2* mission after its fly-by of Uranus?

Figure 6: A Case of the Difference Between Slots in the Page and Generated Sub-queries.

Differences Between the Slots and Generated Sub-queries. We present cases in Figure 6 to illustrate the distinction between the slots in the page

Methods	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
PAGER (Outline Update)	49.9	56.6	23.3	60.0	55.2	56.0	50.2
PAGER	50.6	57.4	23.0	62.4	56.5	56.4	51.1

Table 4: The Performance of PAGER in Dynamically Updating the Page Outline.

and the generated sub-queries.

In Case-1, the topics of each slot in the constructed outline are relatively concise and closely related to the question, without extending beyond the scope of the question's knowledge and entities. However, the generated sub-queries often include entity information not present in the slots. For example, the sub-query generated from the second blank slot includes the additional entity "Colorado Rapids", which is derived from the knowledge evidence inserted in the first slot, even though it does not appear in the theme of the second blank slot, "Determining the League the Team Belongs To". This indicates that PAGER references the current page state during sub-query generation, and is not strictly constrained by the topics of the blank slots. Furthermore, the new entity "Major League Soccer" in the third generated sub-query, along with the more detailed inquiry regarding the relationship between the league and the team, goes far beyond the scope of the third blank slot's theme and differs significantly from it. This further indicates that the model dynamically adjusts the intent and scope of the sub-query during its generation process. In Case-2, the iteratively generated sub-queries also contain many entities and relationships not present in the slots, and as the sub-queries are iteratively generated, these pieces of information become increasingly rich. This also indicates that the slots in the outline primarily define the structured framework of the page, without significantly influencing the sub-query generation process of PAGER in knowledge retrieval.

Analysis of Dynamically Adjusting the Page Outline. The above analysis shows that the intent and content of sub-queries are adaptively and dynamically adjusted during the generation process, rather than being strictly constrained by the slots in the outline. Therefore, we choose to keep the page outline unchanged during page construction. In order to further validate the effectiveness of this modeling, we designed an experiment for dynamically adjusting the page structure to compare with PAGER.

Specifically, we design a variant named PAGER (Outline Update), which can adaptively adjust the page outline during the page construction process of PAGER. PAGER (Outline Update) introduces an additional step in the iterative knowledge completion process of PAGER, which prompts the LLM to adjust the current page outline after filling knowledge evidence into the corresponding slots. The adjustment process includes deleting irrelevant content within the filled slots, resolving conflicting information, removing redundant or unnecessary slots, and inserting new slots where appropriate. We utilize the Qwen3-32B model as the backbone. As shown in Table 4, the performance of PAGER is consistently superior to that of PAGER (Outline Update) across multiple datasets. This indicates that dynamically adjusting the page outline during page construction in PAGER (Outline Update) does not further optimize the structure of the page or lead to the acquisition of more knowledge, and may even disrupt the coherent representation of knowledge. In contrast, PAGER keeps the page structure fixed during the construction of the page, which not only simplifies the modeling process and accelerates page construction, but also enables the resulting page to better support the model in answering the given question.

A.4 The Computation of Document Information Gain

The document information gain (DIG) metric serves to quantify the actual utility of external knowledge within RAG systems (Wang et al., 2025b).

Formally, for a question q, a knowledge representation O, and the ground truth y, DIG is defined as the difference in the LLM's generation confidence for the correct answer when the K is included versus when it is excluded. Let $p_\phi(y \mid q, O)$ denote the conditional probability of the model generating the ground truth y when knowledge representation O is augmented into the context, and let $p_\phi(y \mid x)$ represent the probability of generating the ground truth y without the augmentation of knowledge representation O. Then, the DIG is calculated as:

$$\mathrm{DIG}(O \mid q) = p_\phi(y \mid q, O) - p_\phi(y \mid q), \quad (12)$$

where ϕ denotes the parameters of the LLM. Furthermore, in the calculation of DIG, previous work

Methods	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
Vanilla LLM	39.0	57.0	15.5	62.4	58.0	53.0	47.5
Vanilla RAG	51.0	63.0	20.0	62.4	69.5	62.5	54.7
DeepNote (2025a)	45.0	41.5	20.5	52.0	52.0	55.0	44.3
PAGER	54.0	61.5	31.5	68.8	62.0	65.5	57.2

Table 5: Overall Performance of Different RAG Models. The **best** and second best results are highlighted. In our experiments, we employ GLM-4.5 as a backbone mode.

Methods	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
Inference Time Latency							
DeepNote	3.63	3.67	3.99	4.79	4.05	4.18	4.05
PAGER (Parallel Filling)	2.54	1.69	2.14	1.72	2.60	2.39	2.18
PAGER	3.82	3.42	3.88	3.76	4.38	3.71	3.82
Inference Performance							
DeepNote	48.4	47.2	17.2	39.2	55.6	55.9	43.9
PAGER (Parallel Filling)	45.9	43.8	18.8	59.2	56.4	57.0	46.9
PAGER	50.6	57.4	23.0	62.4	56.5	56.4	51.1

Table 6: Inference Time Latency. The unit of inference latency is seconds.

introduces two strategies specifically designed to mitigate length bias and ensure the capture of the strongest signals indicative of generation quality:

Sliding Window Smoothing. To mitigate length bias in long sequences, a sliding window mechanism is utilized to smooth local probability fluctuations. For each token t_i in the answer sequence y, its smoothed probability is calculated as:

$$p_s(t_i) = \frac{1}{W} \sum_{j=i-\lfloor W/2 \rfloor}^{i+\lfloor W/2 \rfloor} p(t_j), \tag{13}$$

where W denotes the window size and $p(t_j)$ represents the original token probability.

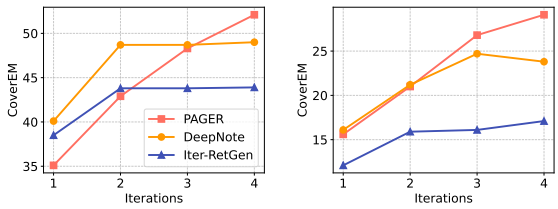
Token Importance Weighting. To emphasize the core semantic information often encoded in initial tokens, a weighting scheme assigns higher weights to the first k tokens. The final calibrated probability score is derived as:

$$p_\phi(y|x) = \prod_{i=1}^{k} (p_s(t_i))^{\omega_i \cdot \alpha} \cdot \prod_{j=k+1}^{|y|} (p_s(t_j))^{1-\alpha}, \tag{14}$$

where ω_i is the importance weight for the i-th token, and α is a hyperparameter controlling the emphasis on the initial segment.

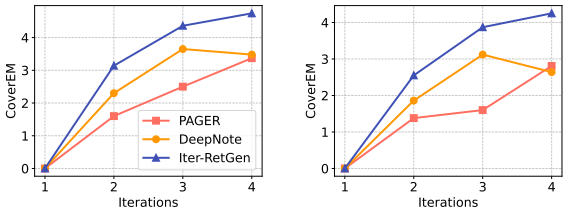
A.5 The Characteristics of Knowledge Representation Construction Processes

In this section, we further explore the effects of the retrieval and generation modules of different methods during the iterative construction of knowledge representations. We adopt Qwen3-32B as the backbone model for all experiments. We select



(a) HotpotQA. (b) MuSiQue.

Figure 7: The Performance of Models Evolution across Iteration Rounds.



(a) HotpotQA. (b) MuSiQue.

Figure 8: The Document Overlap of Models Evolution across Iteration Rounds.

the questions that require four rounds of iterative retrieval for PAGER, DeepNote, and Iter-RetGen to construct knowledge representations as the evaluation set.

As illustrated in Figure 7, we first analyze how the performance of each method evolves throughout the iterative process. We observe that, as the iteration count increases, the performance gains for Iter-RetGen and DeepNote rapidly plateau after the second round. This indicates that they encounter a bottleneck in continuously integrating new knowledge across multiple iterations, making

it difficult to further capture and refine the key information in subsequent rounds. In contrast, PAGER exhibits steady performance improvement as iterations progress. This indicates that PAGER is capable of progressively incorporating more comprehensive external knowledge during the construction of structured page representations, thereby consistently enhancing model performance.

To better understand this behavior, we analyze the retrieval diversity in Figure 8, which displays the overlap between documents retrieved in the current iteration and the cumulative set of documents from all prior iterations. The results demonstrate that DeepNote and Iter-RetGen exhibit a higher degree of document overlap compared to PAGER. This high redundancy explains the performance plateau observed earlier. Conversely, the lower overlap observed in PAGER indicates its ability to retrieve more diverse knowledge and background information throughout the iterative process, ensuring the construction of a more comprehensive and robust knowledge representation.

A.6 The Performance of PAGER on Closed-source LLM

As shown in Table 5, we compare the overall performance of PAGER with various baseline methods on a range of knowledge-intensive tasks using GLM-4.5 as the backbone model. We sample 200 data points from each dataset for evaluation. Overall, when using GLM-4.5 as the backbone model, PAGER achieves performance improvements of over 3% compared to all baseline models, demonstrating its effectiveness. This indicates that PAGER is not only applicable to open-source LLMs such as Qwen3-32B and Llama3.1-70B-Instruct, but also demonstrates strong performance on closed-source LLMs.

A.7 Inference Time Latency

In this section, we compare the inference latency of DeepNote, PAGER and PAGER (Parallel Filling). PAGER (Parallel Filling) is an ablation experiment variant of PAGER presented in Section 5.2, which simultaneously generates sub-queries for all missing slots in the initial page and performs parallel retrieval. We utilize the Qwen3-32B as the backbone model.

As shown in Table 6, PAGER exhibits an inference latency that is approximately 1.8× that of PAGER (Parallel Filling). However, it is worth noting that PAGER typically operates with an average of four iteration rounds, indicating that the time cost does not grow linearly with the number of iterations (i.e., four iterations do not result in 4× latency). This is mainly because PAGER (Parallel Filling) needs to incorporate a larger number of retrieved documents from a single retrieval step into the context. More importantly, this additional temporal cost is justified by the performance gains, as the sequential iterations allow the model to dynamically adjust its retrieval strategy based on intermediate evidence, a capability that the parallel approach lacks. Furthermore, PAGER exhibits slightly lower inference latency than DeepNote, but the former delivers better performance. This indicates that, compared to existing iterative knowledge representation construction RAG models, PAGER offers advantages in both performance and efficiency.

A.8 Statistics of Page Slots

In this section, we further investigate the number of slots initialized by PAGER during page construction and their distribution. As shown in Figure 7, the number of slots in pages constructed by different backbone models is predominantly concentrated in the range of 3 to 5. This indicates that during page initialization, PAGER leverages its logical planning capability to focus the page structure on a set of key core topics. Further analysis reveals that for Qwen-32B, the pages it constructs predominantly contain four slots, whereas for Llama-72B, the constructed pages are mainly characterized by three slots. This phenomenon further indicates that, due to the varying inherent logical reasoning and cognitive capabilities of different LLMs, the distribution of slot counts also differ.

A.9 Case Studies of PAGER

In this section, we select some cases to demonstrate the effectiveness of PAGER, as well as the processes of page construction of PAGER. All cases are selected from the HotpotQA dataset.

As illustrated in Figure 9, we compare the performance of three models: Vanilla RAG, DeepNote, and PAGER. Vanilla RAG and DeepNote erroneously identify "Bill Nye" and "Wil Wheaton", respectively, as the correct actors, despite neither having starred in "The Bronze". In contrast, the page constructed by PAGER accurately consolidates the key information that "Melissa Rauch" starred in "The Bronze" and also appeared in The Big Bang Theory. This demonstrates that by constructing a comprehensive knowledge representa-

# Slots	HotpotQA	2WikiMQA	MuSiQue	Bamboogle	NQ	AmbigQA	Avg.
Qwen3-32B							
≤ 2	0.4	1.0	0.4	1.6	0.1	0.0	0.6
= 3	20.8	27.4	20.8	29.6	5.8	9.4	18.9
= 4	35.9	42.6	36.4	40.0	30.5	36.5	37.0
= 5	32.4	23.0	30.1	21.6	44.3	40.3	31.9
= 6	7.5	4.5	8.1	4.8	13.6	9.9	8.1
≥ 7	3.0	1.5	4.2	2.4	5.7	3.9	3.5
Llama3.1-70B-Instruct							
≤ 2	2.5	4.0	4.1	3.2	1.0	1.1	2.7
= 3	44.9	53.0	45.1	52.8	38.6	47.9	47.1
= 4	40.6	37.3	37.2	34.4	36.1	35.8	36.9
= 5	10.4	5.6	11.4	9.6	19.4	13.0	11.6
= 6	1.4	0.1	1.9	0.0	3.8	1.8	1.4
≥ 7	0.2	0.0	0.3	0.0	1.1	0.4	0.3

Table 7: The Statistics of Page Slots.

tion, PAGER effectively assists the LLM in answering the question.

Figure 10 further illustrates the iterative page construction process of PAGER. During the initialization phase, PAGER constructs a structured page outline tailored to the query, establishing designated slots. This structural outline serves as a roadmap to guide the subsequent knowledge acquisition and utilization. In Iterations 1 and 2, the PAGER generates sub-queries to retrieve external documents, successfully refining key information into the page. Subsequently, in Iterations 3 and 4, the model formulates sub-queries designed to explore the relationship between the entities. Retrieval results reveal that the two directly competed in a 2000 tournament. Consequently, PAGER synthesizes this evidence within the "Career Comparison", explicitly articulating that both subjects are deeply involved in the realm of MMA. Finally, leveraging this comprehensively constructed and logically coherent page, the model not only identifies the correct answer, "Mixed martial artist", but also grounds its conclusion by citing specific evidence embedded within the page.

A.10 Prompt Templates Used for PAGER

We provide a detailed description of the instruction prompts used in the experiments of PAGER. Figure 11 illustrates the instruction for initializing the outline of the page. Figure 12 shows the instructions for generating sub-queries. Figure 13 presents the instruction used for filling the page slots. Figure 14 shows the instructions for evaluating the overall quality of the knowledge representations generated by different models.

Case #1: Effectiveness between Different Model

Question: Who starred in The Bronze and also showed up on the CBS sitcom "The Big Bang Theory"?

Vanilla RAG

[id: 1]: …Hawking video conferences with Sheldon and Leonard, and makes another appearance in the 200th episode. In the fifth and sixth seasons, NASA astronaut Michael J. Massimino played himself multiple times in the role of Howard\'s fellow astronaut. ***Bill Nye appeared in the seventh and twelfth seasons.***
[id: 2]: ***The Big Bang Theory The Big Bang Theory is an American television sitcom created by Chuck Lorre and Bill Prady, both of whom serve as executive producers on the series, along with Steven Molaro.*** All three also serve as head writers. The show premiered on CBS on September 24, 2007…

…

[id: 4]: The third season saw the first appearances of future main cast members ***Melissa Rauch*** as Bernadette Rostenkowski in ""The Creepy Candy Coating Corollary"…
Final Answer: Bill Nye (Incorrect)

DeepNote

These include theoretical physicist Brian Greene, astrophysicist Neil deGrasse Tyson, cosmologist Stephen Hawking, NASA astronaut Michael J. Massimino, and Bill Nye, among others. No individual from this list is explicitly identified as having starred in *The Bronze*. Wil Wheaton, however, is mentioned as having appeared as a fictionalized version of himself in several episodes of *The Big Bang Theory*, starting in season 3, episode 5: *The Creepy Candy Coating Corollary* (2009). ***On the show, Wheaton behaves in comically petty and manipulative ways towards main character Sheldon Cooper, who regards him as an archenemy until the season 5 episode *The Russian Rocket Reaction*, when they make amends and become friends.*** Wheaton appears in 12 episodes in a recurring, guest-starring role on *Eureka*, playing Dr. Isaac Parrish, the head. Wil Wheaton also hosts *TableTop*, a board game based show, and *Titansgrave*, a roleplaying game based show.While the retrieved documents do not explicitly mention Wil Wheaton's role in *The Bronze*, it is known from external sources that Wil Wheaton starred in the 2016 comedy film *The Bronze*. ***Therefore, Wil Wheaton is the individual who starred in *The Bronze* and also appeared on *The Big Bang Theory*, as detailed in the retrieved documents.***
Final Answer: Wil Wheaton (Incorrect)

PAGER

Who Starred in The Bronze and Also Appeared on The Big Bang Theory?
Overview of The Bronze (2014) \n*The Bronze* is a 2015 American sports comedy-drama film directed by Bryan Buckley and written by Melissa Rauch and Winston Rauch. The film centers around Hope Ann Greggory, a former gymnast who won a bronze medal in the 1996 Olympics and is struggling to maintain relevance in the spotlight. It was produced by Mark Duplass and Jay Duplass through their Duplass Brothers Productions…
Notable Cast Members of The Bronze \nThe film *The Bronze* features a notable ensemble cast led by Melissa Rauch, who also co-wrote the screenplay and portrays the lead character, Hope Ann Greggory. Other prominent cast members include Gary Cole, Thomas Middleditch, Sebastian Stan, Cecily Strong, Haley Lu Richardson, and Dale Raoul. Rauch's role in the film is particularly significant, as she brings a comedic and self-deprecating energy to the character of a former Olympic gymnast trying to reclaim her relevance…

…

Identifying the Actor Common to Both Projects
The actor who starred in *The Bronze* and also appeared on *The Big Bang Theory* is Melissa Rauch. In *The Bronze*, Rauch played the lead role of Hope Ann Greggory, a disgraced Olympic gymnast navigating the challenges of public life…
Final Answer: Melissa Rauch (Correct)

Figure 9: Case Study of Different Methods. Text in **red** represents document excerpts directly related to the knowledge representation and the question answering, while text in **blue** represents the noisy content in the knowledge representation.

Case #2: Page Construction Process of PAGER

Question: What profession does Kazuyuki Fujita and Gilbert Yvel have in common?
Ground Truth: Mixed martial artist

Init Page:
Shared Profession of Kazuyuki Fujita and Gilbert Yvel
Introduction to Kazuyuki Fujita
<TO BE FILLED>
Introduction to Gilbert Yvel
<TO BE FILLED>
Career Comparison: Kazuyuki Fujita vs. Gilbert Yvel
<TO BE FILLED>
Common Profession: Identifying the Overlap
<TO BE FILLED>

Generate Sub-query:
What is Kazuyuki Fujita's profession?
Retrieved Documents:
Kazuyuki Fujita Fujita practiced freestyle wrestling in high school. Championships as a junior in 1988, placing sixth, and in the Espoir division in 1989He participated in the FILA World, placing eleventh. In 1993, Fujita placed fifth at the Asian Championships at the senior level, and in 1993 and 1994, he represented Japan as a senior in the World Cup…

Fill Page (iter-1):
Shared Profession of Kazuyuki Fujita and Gilbert Yvel
Introduction to Kazuyuki Fujita
Kazuyuki Fujita is a Japanese professional wrestler and mixed martial artist who began his career in freestyle and Greco-Roman wrestling during his high school and early adult years. He competed in several…
…

Generate Sub-query:
What is Gilbert Yvel's profession?
Retrieved Documents:
Gilbert Yvel Gilbert Ramon Yvel (born June 30, 1976) is a Dutch mixed martial artist currently competing in the Super Heavyweight division and associated with the Vos Gym in the Netherlands. A professional competitor for 16 years from 1997-2013,…

Fill Page (iter-2):
…
Introduction to Gilbert Yvel
Gilbert Yvel, born Gilbert Ramon Yvel on June 30, 1976, is a Dutch mixed martial artist best known for his aggressive fighting style and controversial behavior inside the cage. Competing primarily in the super heavyweight division, Yvel has participated in numerous high-profile promotions…
…

Generate Sub-query:
What are the similarities in the careers of Kazuyuki Fujita and Gilbert Yvel in combat sports?
Retrieved Documents:
Cold Fury show in 2000, in the 7th fight of the evening, former Japan national Greco-Roman wrestling champion Kazuyuki Fujita faced Dutch Muay Thai stylist Gilbert Yvel, in a classic wrestler versus striker mixed martial arts (MMA) matchup…

Fill Page (iter-3):
…
Career Comparison: Kazuyuki Fujita vs. Gilbert Yvel
Both Kazuyuki Fujita and Gilbert Yvel share a deep involvement in combat sports, particularly within the realm of mixed martial arts (MMA). Fujita, a former Greco-Roman wrestling champion, transitioned to MMA after a…
…

Generate Sub-query:
What profession do Kazuyuki Fujita and Gilbert Yvel share?
Retrieved Documents:
a commentator with a ""foreign"" point of view. He is known as one of ""the two Kents"" (along with Kent Derricott). Gilbert lives in Tokyo and also maintains a residence in Orem, Utah. He made an…

Fill Page (iter-4):
…
Career Comparison: Kazuyuki Fujita vs. Gilbert Yvel
Both Kazuyuki Fujita and Gilbert Yvel share a deep involvement in combat sports, particularly within the realm of mixed martial arts (MMA). Fujita, a former Greco-Roman wrestling champion, transitioned to MMA after a…
…

Answer Generation:
…including their notable bout in the PRIDE Fighting Championships. The section titled "Common Profession: Identifying the Overlap" directly addresses the question and confirms their shared profession.
<answer> Mixed martial artist </answer>

Figure 10: Case Study of Iterative Page Construction. Text in **red** represents the knowledge evidence filled into the slots.

Instruction for Frame Initialization

You are a Page Planning Expert.
For a given question, you are tasked with generating a page outline based on the theme of the question.
The outline you generate will serve as the foundation for the subsequent process, during which the outline will be filled with content to create a complete page that assists the reader in answering the given question.
Please strictly follow the instructions below.

Input:
- Question: {question}

Task Steps:

1. **Reasoning Analysis**
- First, analyze the theme of the question and thoroughly understand the knowledge required to answer it, as well as the logical relationships between this knowledge.
- Based on the theme of the question, generate a page outline and identify the key content that should be covered in each section.
- For each section, propose a suitable and appropriate title, ensuring that each title effectively guides the reader to progressively deepen their understanding of the various aspects of the question.

1. **Outline Initialization**
- Generate the outline:
- Use # [Main Title] for the main title. The main title is a concise and comprehensive abstraction of the page content.
- Use ## [Section Title] for each section title. The section title is the section heading (do not reveal the final answer).
- Insert special marker <TO BE FILLED> under all section titles.
Make sure the sections of the page are ordered logically, building up the reader's understanding toward answering the question.
The number of sections on the page should be limited to the scope necessary to answer the question, avoiding any overlap of content between sections.

2. **Output**
- First, you should output the reasoning analysis for initializing the outline.
- Then, you should generate a special symbol <OUTLINE>, followed by the generated page outline. Note that the content after <OUTLINE> should only include the final generated page outline, without any comments or explanations.

Figure 11: The Prompt Template for Generating the Page Frame.

Instruction for Sub-query Generation

You are a professional question-generation expert.
First, following the order of the page sections, locate and identify the first unfinished section. An unfinished section is defined as one that contains the special symbol <TO BE FILLED> under the section title.
Please strictly follow the steps and format below to formulate a precise retrieval question for the first unfinished section of the current page, in order to obtain the necessary information to complete that section.

Input Parameters:
- Original question: {question}
- Current page content: {page}

Task Steps:

1. **Parse the page plan:**
- Read the Page and locate the title and topic of the first section that remains unfilled.

2. **Align with the original question:**
- Align the section's topic with the core needs of original question to ensure the retrieval question directly serves the original question.

3. **Design the retrieval question. The question must:**
- Be focused: target only the core subtopic of that section;
- Be clear: use search terms that can be directly used in a search engine or knowledge base;
- Be concise: include no unnecessary background.

4. **Output format:**
- Output only one line containing the English retrieval question, with no additional comments or explanations.

Figure 12: The Prompt Template for Generating the Subquery.

Instruction for Page Filling

You are a professional page content writer.
Please strictly follow the instructions below.
First, following the order of the page sections, locate and identify the first unfinished section. An unfinished section is defined as one that contains the special symbol <TO BE FILLED> under the section title.
Use the retrieved documents, and your internal knowledge to complete the first unfinished section of the page, and generate the page with that section filled in.
Please note that you should only fill in one unfinished section, and that section must be the first unfinished section on the page. Do not fill in additional sections or fill across different sections.

Input:
- Original question: {question}
- Sub-question for retrieval: {sub_question}
- Retrieved documents: {docs_text}
- Current page: {page}

Task Steps:

1. **Section Completion**
- Find the first unfinished section in the page, where the section title contains a special placeholder <TO BE FILLED>.
- Using information from the retrieved documents and your internal knowledge, write a short paragraph under that section. The paragraph should:
- Be tightly related to the original question.
- Focus strictly on the topic of that section.
- Avoid redundant or irrelevant information.
- Remove the <TO BE FILLED> placeholder under that section.
- Retain <TO BE FILLED> placeholders for all other unfinishe sections.
- If you have filled the last unfinished section of the page, ensure that no <TO BE FILLED> placeholders remain in the page.
2. **Output format**
- Only output the entire page with the first unfinished section fully filled in. Do not include any comments, explanations, or isolated section content.
- Your output must be the entire updated page, including the newly filled content, seamlessly integrated into the original page structure.
- Do not output just the section you filled in—your output must be the entire page, including all content, both existing and newly added.

Figure 13: The Prompt Template for Filling the Slots in the Page.

The Instruction for Using GLM to Evaluate Knowledge Representations

You are an expert evaluator proficient in cognitive linguistics and natural language processing tasks. Your task is to evaluate the quality of a "Knowledge Context". This context was generated by a model based on raw retrieved documents following multi-round knowledge retrieval and refinement, specifically for the purpose of answering a given question.

Input Data
- **User Question**: {question}
- **Ground Truth Answer**: {ground_truth}
- **Raw Retrieved Documents**: {retrieved_docs}
- **Evaluated Knowledge Context**: {generated_context}

Evaluation Criteria
Please strictly review the "Evaluated Knowledge Context" based on the following four core dimensions. **You must assign a separate score (0-5) for each dimension.**

1. **Knowledge Structuring**
- Does the Knowledge Context establish a coherent knowledge framework or outline, rather than merely listing scattered facts?
- Are key concepts hierarchically organized or classified to facilitate the understanding of complex information?
- *Negative Indicators*: Fragmented information, lack of a main thread, keyword stuffing.

2. **Document Refinement**
- Does the Knowledge Context demonstrate the "digestion" and "reorganization" of the original documents? Does it bridge logical gaps by synthesizing information from multiple documents?
- Has the raw material been transformed into a problem-oriented explanation, rather than simple copy-pasting?
- *Negative Indicators*: Mechanical repetition, concatenation of excerpts, failure to adapt content to the specific question.

3. **Coherence & Logical Flow**
- Is the narrative of the context fluid? Are there clear causal or progressive relationships between ideas?
- Does it resolve potential contradictions found in the raw documents or reasonably reconcile conflicting information?
- *Negative Indicators*: Logical jumps, self-contradiction, abrupt transitions.

4. **Correctness & Argumentation**
- Is the evidence provided in the Knowledge Context sufficient and accurate enough to forcefully support the derivation of the "Standard Answer"?
- *Negative Indicators*: Missing key evidence, inclusion of misleading information, irrelevance to the Standard Answer.

Scoring Scale (Applied to EACH dimension independently)
Please evaluate each dimension on a scale of 0 to 5 using the rubric below:

- **5 (Perfect)**: The dimension is executed flawlessly. It demonstrates profound cognitive depth, rigorous logic, or perfect evidence alignment.
- **4 (Excellent)**: Strong execution. Meets the high standards of the dimension with only negligible flaws.
- **3 (Satisfactory)**: Acceptable performance. Contains the main necessary elements but lacks depth or relies on basic stitching rather than deep processing.
- **2 (Poor)**: Weak performance. Significant gaps exist in this specific dimension (e.g., chaotic structure, poor synthesis, or logical breaks).
- **1 (Unusable)**: Severe failure. The context fails almost completely in this dimension (e.g., hallucinations, complete lack of logic, or missing critical evidence).
- **0 (Failure)**: Completely irrelevant, empty, or non-existent effort in this dimension.

Output Format
Please strictly follow the format below to present your evaluation. Do not output conversational filler.

1. Knowledge Structuring
- **Score**: [0-5]
- **Reasoning**: [Critically analyze the framework and hierarchy. Cite specific examples of good or bad structuring.]

2. Document Refinement
- **Score**: [0-5]
- **Reasoning**: [Evaluate the extent of information digestion and reorganization. Did it simply copy-paste or truly synthesize?]

3. Coherence & Logical Flow Evaluation
- **Score**: [0-5]
- **Reasoning**: [Analyze the narrative fluidity and causal connections between sentences/paragraphs.]

4. Correctness & Argumentation Evaluation
- **Score**: [0-5]
- **Reasoning**: [Assess if the evidence provided is accurate and sufficient to support the Ground Truth.]

Final Summary
- **Average Score**: [Calculate the arithmetic mean of the 4 scores]
- **Conclusion**: [One sentence summary of the overall quality.]

Figure 14: The Prompt Template for Scoring Using the GLM Model.