

# SurveyG: A Multi-Agent LLM Framework with Hierarchical Citation Graph for Automated Survey Generation

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## Abstract

Large language models (LLMs) are increasingly adopted for automating survey paper generation [9, 10, 15, 16, 20]. Existing approaches typically extract content from a large collection of related papers and prompt LLMs to summarize them directly. However, such methods often overlook the structural relationships among papers, resulting in generated surveys that lack a coherent taxonomy and a deeper contextual understanding of research progress. To address these shortcomings, we propose **SurveyG**, an LLM-based agent framework that integrates *hierarchical citation graph*, where nodes denote research papers and edges capture both citation dependencies and semantic relatedness between their contents, thereby embedding structural and contextual knowledge into the survey generation process. The graph is organized into three layers: **Foundation**, **Development**, and **Frontier**, to capture the evolution of research from seminal works to incremental advances and emerging directions. By combining horizontal search within layers and vertical depth traversal across layers, the agent produces multi-level summaries, which are consolidated into a structured survey outline. A multi-agent validation stage then ensures consistency, coverage, and factual accuracy in generating the final survey. Experiments, including evaluations by human experts and LLM-as-a-judge, demonstrate that SurveyG outperforms state-of-the-art frameworks, producing surveys that are more comprehensive and better structured to the underlying knowledge taxonomy of a field.

## CCS Concepts

• Computing methodologies → Information extraction.

\*Both authors contributed equally to this research.

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## Keywords

Automated Survey Generation, Large Language Model, Literature Synthesis, Multi-agent, Hierarchical Graph Representation

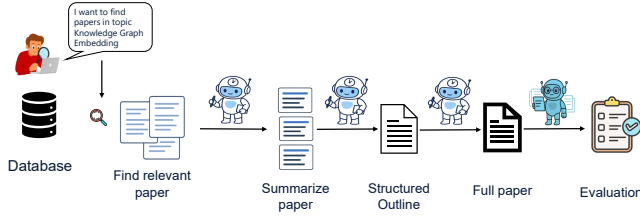
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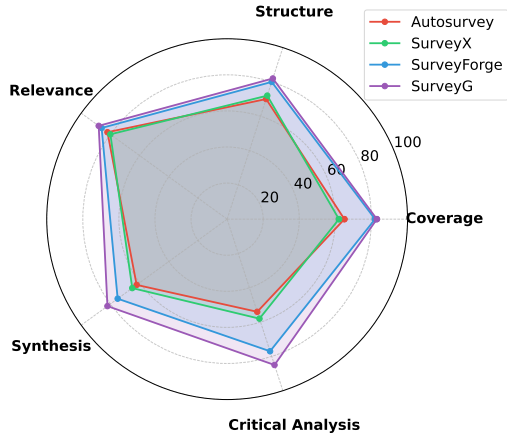
## 1 Introduction

The exponential growth of research publications, particularly in rapidly evolving fields such as Artificial Intelligence [7], has made it increasingly difficult for researchers to keep pace with new developments [15, 16]. While survey papers serve as invaluable resources by synthesizing existing knowledge and identifying emerging trends, their manual construction is costly, time-consuming, and often unable to keep up with the overwhelming influx of literature [9]. Although large language models (LLMs) offer promising text generation capabilities, they face critical limitations in handling massive reference sets, maintaining academic rigor, and providing up-to-date knowledge [6, 18]. These challenges underscore the urgent need for an automated survey generation framework that can efficiently retrieve, organize, and synthesize literature into coherent, high-quality surveys tailored to users' research interests.

Some recent studies [9, 10, 15, 20] have proposed autonomous survey generation frameworks based on user queries, following the basic pipeline illustrated in Figure 1. While these approaches represent promising progress, they exhibit two key limitations. **Firstly**, they neglect the relationships between papers, such as citation links, methodological connections, or subtopic dependencies, which are essential for understanding how works build upon one another, improve over foundational methods, and collectively shape research trends. **Secondly**, these frameworks employ a naive strategy for constructing structured outlines or full survey papers, simply concatenating summaries of individual papers. This not only exacerbates the long-context problem in LLMs but also fails to exploit the hierarchical organization of related works within subtopics.



**Figure 1: Overview of the standard automated survey pipeline, which involves three core stages: (1) preparing relevant papers, (2) generating a structured outline that defines sections and subsections, and (3) composing the full survey.**



**Figure 2: Evaluation of generated surveys across multiple metrics using LLM-as-a-judge, validated by human experts.**

To address these limitations, we propose **SurveyG**. This autonomous survey generation system emphasizes knowledge representation of retrieved papers and employs hierarchical summarization to construct well-structured outlines, which are an essential component of high-quality surveys. In detail, we design an LLM-based multi-agent framework that represents knowledge using a hierarchical citation graph, where nodes correspond to papers and edges capture both citation relationships and semantic similarity. The graph is organized into three layers: **Foundation**, **Development**, and **Frontier** to reflect the progression of research from seminal contributions to incremental improvements and emerging directions. By combining horizontal searches within layers and vertical traversals across layers, our framework generates multi-aspect summaries that are subsequently consolidated into a structured survey outline via a multi-agent framework.

We evaluate SurveyG on 10 computer science topics from the SurGE benchmark [10], comparing its survey generation performance with existing state-of-the-art frameworks [9, 15, 20]. Following prior work, we assess outlines along five dimensions: *Coverage*, *Structure*, *Relevance*, *Synthesis*, *Critical Analysis*. Details of the experimental setup are provided in Section 4. As shown in Figure 2, while baseline methods achieve reasonable performance in Relevance and partially in Structure and Coverage, they perform significantly worse in Synthesis and Critical Analysis, primarily

due to their inability to model inter-paper relationships and the limitations imposed by long-context inputs.

In conclusion, this work presents three key contributions to automated survey generation. First, we introduce a hierarchical citation graph representation that models both citation and semantic relationships among papers. Second, we develop a graph-based traversal mechanism that operates across this hierarchy to produce diverse and multi-aspect summarizations, effectively capturing the methodological foundations, developmental trends, and frontier directions of a research field. Third, we design a multi-agent framework that combines retrieval-augmented generation (RAG) with pre-built hierarchical summaries as memory, allowing the system to automatically construct coherent and comprehensive survey drafts grounded in verifiable evidence.

## 2 Related works

### 2.1 Long-form Text Generation

LLMs have achieved remarkable progress, yet generating long-form, coherent, and logically structured documents remains a persistent challenge [2, 3, 6]. Recent works have explored different strategies to address the long-context problem. For example, Chain-of-Agents [21] introduces a multi-agent collaboration framework where worker agents process segmented portions of text and a manager agent synthesizes them into coherent outputs, alleviating focus issues in long contexts. LongAlign [1] proposes a recipe for long context alignment, combining instruction data construction, efficient batching, yielding strong gains on queries up to 100k tokens. Complementary to these, Xu et al. [19] systematically examine the trade-offs between retrieval-augmentation and context-window extension, showing that hybrid approaches can outperform both strategies alone. However, existing approaches often rely on raw reference texts, leading to inefficient retrieval, limited context utilization, and poor structural coherence in survey-like outputs.

### 2.2 Automatic Survey Generation

The automatic generation of literature reviews has been studied for over a decade, starting with multi-document summarization techniques that produced unstructured related work sections. Early systems, such as IBM Science Summarizer [4], focused on summarizing scientific articles, while more recent LLM-based methods like ChatCite [8] and Susnjak et al. [12]’s domain-specific fine-tuning advanced the generation of comparative and knowledge-enriched reviews. Despite these advances, such methods primarily tackle summarization rather than the creation of fully structured survey papers. More recent systems, including AutoSurvey [15], InteractiveSurvey [16], SurveyForge [20], and SurveyX [9], propose end-to-end pipelines integrating RAG, clustering, or multi-agent strategies to automate survey construction. These methods improve structural coherence and formatting consistency while scaling to long-form survey content. Nevertheless, most frameworks still restrict users to fixed input-output modes, overlooking relationships among papers and limiting interactivity, which often results in surveys that lack flexibility, relational awareness, and depth.

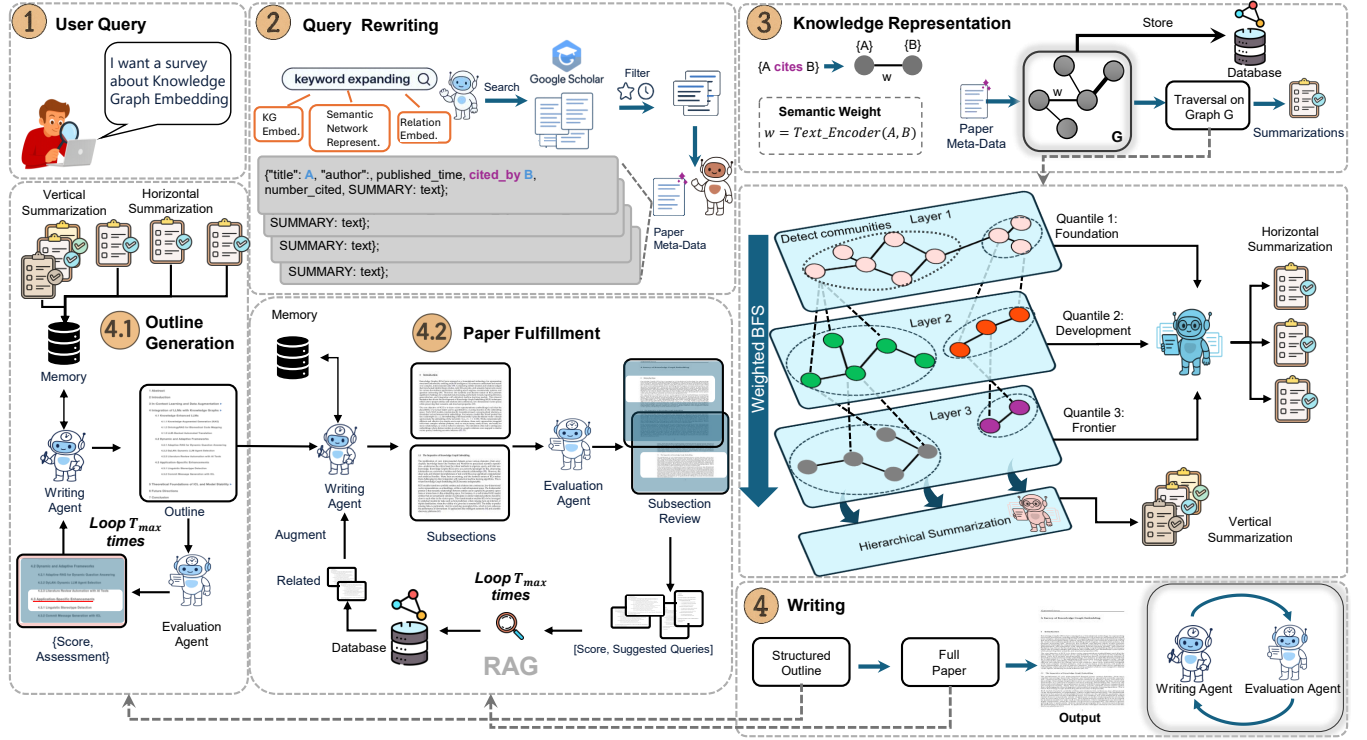


Figure 3: Starting from a user’s query, SurveyG retrieves and filters relevant papers (step 1-2), builds a hierarchical citation graph, and applies horizontal and vertical traversals to produce multi-aspect summaries (step 3). A multi-agent framework then leverages these pre-built summaries to produce a structured outline and a complete survey paper (step 4).

### 3 Methodology

We introduce **SurveyG**, an automated survey generation framework that operates in two main phases. The **Preparation Phase** involves retrieving relevant papers, summarizing their content, constructing a hierarchical citation graph, and extracting relationships by traversing the graph. The **Generation Phase** focuses on producing a structured outline and composing a complete survey by integrating instruction prompting within a multi-agent framework. An overview of SurveyG is illustrated in Figure 3.

#### 3.1 Preparation Phase

We represent the relationships among papers using a *hierarchical citation graph*, where nodes correspond to academic papers and edges capture both citation links and semantic similarity, each weighted by a value  $w$ . Each node is further assigned to one of three layers: **Foundation**, **Development**, or **Frontier**, which reflect the role of the paper in the progression of research. Formally, the hierarchical citation graph is defined as  $G = (V, E, L)$ , where  $V$  denotes the set of nodes (papers),  $E \subseteq V \times V$  is the set of directed or undirected edges encoding citation or semantic relationships, and  $L : V \rightarrow \{\text{Foundation, Development, Frontier}\}$  is a layer assignment function. For each node  $v_i \in V$ , we associate a corresponding document  $d_i \in D$ , where  $D$  is a database storing the complete content of all papers. In addition, each node  $v_i \in V$  is equipped with

attributes that include a summarization of  $d_i$  as well as metadata such as the paper’s title and publication year.

**3.1.1 Searching Relevant Paper.** Given a user query  $q$ , our goal is to construct a hierarchical citation graph  $G$  that encompasses all relevant papers while capturing the evolutionary trends of research in the field. We first employ an LLM to expand the query into a set of diverse keywords  $\{k_1, \dots, k_n\} = \text{LLM}(q)$ . Using these keywords, we retrieve candidate papers through the crawling module. After collecting the relevant papers, we establish edges between them based on citation links and quantify their semantic relatedness through weighted connections. The weight  $w$  assigned to an edge connecting papers  $v_i$  and  $v_j$  is defined as

$$w = \text{sim}(\text{Text\_Encoder}(v_i), \text{Text\_Encoder}(v_j)), \quad (1)$$

where  $\text{sim}(\cdot)$  denotes the cosine similarity between the text embedding vectors of the two papers. For computational efficiency, embeddings are derived solely from the abstract of each paper, which captures the core conceptual content while minimizing processing overhead.

To better leverage the key content of each paper for survey generation, every node  $v_i$  is enriched with a summarization derived from its corresponding document  $d_i$ . We design specialized prompt templates tailored to different paper types [9] (e.g., surveys, methodological contributions, benchmarks, theoretical works). After this phase, we obtain a flat graph  $\hat{G} = (V, E)$  that encompasses the

papers relevant to the user’s topic along with their relationships. Each node  $v_i \in V$  is associated with a set of attributes defined as

$$A(v_i) = \{\text{metadata}(v_i), \text{summary}(d_i)\},$$

where  $\text{metadata}(v_i)$  contains bibliographic information such as the paper’s title, authors, and publication year, and  $\text{summary}(d_i)$  represents the content-based summarization of the corresponding document. These attributes are also stored in the database  $D$  to facilitate efficient retrieval and analysis.

**3.1.2 Knowledge Representation.** To reflect the developmental progression of research within a topic, we assign each node in the flat graph  $\hat{G} = (V, E)$  to one of three hierarchical layers via a layer assignment function

$$L : V \rightarrow \{\text{Foundation, Development, Frontier}\}.$$

(1) **Foundation Layer.** The foundation layer consists of seminal and high-impact works that form the intellectual backbone of the field. For each paper  $p$ , we define a *trending score* as

$$\text{trend}_{\text{score}}(p) = \frac{\text{citation\_count}(p)}{1 + \text{year\_published}(p)}, \quad (2)$$

where  $\text{year\_published}(p)$  denotes the number of years elapsed since the paper’s publication. Papers are ranked by this score, and the top- $K$  entries constitute the foundation set:

$$V_{\text{foundation}} = \{v_i \in V \mid \text{trend}_{\text{score}}(v_i) \leq K\}.$$

These papers are not only highly cited but also serve as conceptual anchors that establish key paradigms and problem formulations underpinning later research. (2) **Development Layer:** The development layer captures the historical evolution of the field before a time landmark  $T$  (eg, 2025), representing works that refine, extend, or challenge the foundations. Formally,

$$V_{\text{development}} = \{v_i \in V \mid \text{year}(v_i) < T, v_i \notin V_{\text{foundation}}\},$$

These works are often incremental yet essential: they consolidate methodological frameworks, validate empirical findings, and enable the community to mature foundational ideas into established research threads. (3) **Frontier Layer:** The frontier layer reflects the cutting edge of inquiry, consisting of recent contributions that point toward emerging trends and open challenges. It is defined as

$$V_{\text{frontier}} = \{v_i \in V \mid \text{year}(v_i) \geq T, v_i \notin V_{\text{foundation}}\}.$$

Unlike the development layer, frontier works are temporally close to the present and thus provide a window into the current momentum and future trajectories of the domain. After this mapping, the hierarchical citation graph is represented as

$$G = (V, E, L), \quad V = V_{\text{foundation}} \cup V_{\text{development}} \cup V_{\text{frontier}}.$$

Traversing  $G$  along horizontal (intra-layer) and vertical (inter-layer) edges then enables the generation of multi-aspect summaries covering methodologies, developmental trends, and future directions.

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#### Algorithm 1 Vertical Traversal for Multi-Summarization

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1: Input: Citation graph  $G = (V, E, L)$ , foundation papers  $V_{\text{foundation}}$ 
2: Output:  $\{T_{\text{path}}^{(1)}, \dots, T_{\text{path}}^{(K)}\}$ , where  $K = |V_{\text{foundation}}|$ 
3: for all  $s \in V_{\text{foundation}}$  do
4:    $P_1 \leftarrow \{\text{EXTRACT}(s)\}$ 
5:    $P_2 \leftarrow \{\text{EXTRACT}(u) \mid u \in \text{WBFS}(s, \text{Development})\}$ 
6:    $P_3 \leftarrow \{\text{EXTRACT}(w) \mid w \in \text{WBFS}(P_2, \text{Frontier})\}$ 
7:    $T_{\text{dev}} \leftarrow \text{GENERATESUMMARIZE}(P_1 \cup P_2)$ 
8:    $T_{\text{path}} \leftarrow \text{GENERATESUMMARIZE}(T_{\text{dev}}, P_3)$ 
9:   Store  $T_{\text{path}}$  as the summarization for seed  $s$ 
10: end for
11: return  $K$  summarizations  $\{T_{\text{path}}^{(1)}, \dots, T_{\text{path}}^{(K)}\}$ 

```

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You are a research analyst synthesizing papers on the topic [QUERY]. <think> Explain your reasoning for clustering papers into 2–3 subgroups based on methodology, contribution, or thematic focus. </think>

For each subgroup, summarize the shared methodological approaches, thematic contributions, and provide a concise critique comparing the works. Finally, synthesize an overall perspective highlighting how these subgroups collectively operate in the field.

**Figure 4: Horizontal summarization short version prompt.**

**3.1.3 Traversal on Graph Strategy.** We propose a two-stage summarization framework designed to capture both the breadth and depth of the hierarchical citation graph. In the *horizontal stage*, to capture the internal structure of each layer  $V_l$ , we partition it into communities using the Leiden algorithm [13], yielding

$$C_l = \{C_{l,1}, \dots, C_{l,m_l}\}, \quad \bigcup_{j=1}^{m_l} C_{l,j} = V_l.$$

Each community  $C_{l,j}$  corresponds to a coherent research direction formed by citation and semantic proximity. For every community, we query an LLM using a carefully constructed prompt that integrates Plan-and-Solve [14] strategies, along with paper-specific attributes, to generate a synthesized summary:

$$T_{l,j} = \text{LLM}(\{A(v_i) \mid v_i \in C_{l,j}\}),$$

which emphasizes the methodologies and thematic scope of the papers while capturing key relationships among them. This process uncovers sub-directions within the topic and provides a global perspective of how research clusters evolve within each layer. The detailed prompts used for information extraction are provided in Figure 4.

In the *vertical stage*, we aim to model cross-layer dependencies. For each foundation paper, we perform a weighted breadth-first search (WBFS) over its citation paths, where traversal prioritizes semantically relevant nodes according to edge weights. The algorithmic details are provided in Algorithm 1, the full WBFS procedure and prompt design are described in Appendix A. Each resulting path

aggregates the node attributes  $A(v)$  for all  $v$  encountered during the WBFS traversal and places them in the *path* variable. We then apply hierarchical summarization across layers, exploiting temporal progression to mitigate long-context issues and extract key insights more effectively [21]. This process incrementally integrates knowledge from the Development and Frontier layers into path-specific summaries. After the summarization phase, SurveyG ultimately produces  $K + N$  outputs with  $N$  horizontal layer summaries and  $K$  vertical path summaries.

In contrast to earlier frameworks [9, 15, 16, 20] that represent papers as isolated records in a flat database and depend exclusively on RAG-based retrieval, SurveyG organizes the literature within a hierarchical citation graph  $G$ . This representation integrates both citation and semantic connections among papers, allowing the system to capture the logical progression of research topics over time. By traversing this hierarchy, SurveyG produces a series of summarizations across multiple layers, effectively revealing methodological developments, evolutionary patterns, and current research frontiers. Such a design provides a more coherent and interpretable knowledge foundation for automated survey generation.

### 3.2 Generation Phase

We employ a multi-agent conversational framework [17] to guide the generation of survey papers. The system is composed of two complementary agents: a Writing Agent, equipped with memory [11] initialized with  $K + N$  summarizations from the graph traversal phase, and an Evaluation Agent, which leverages the internal reasoning capabilities of LLMs to provide diversity-oriented feedback. Through iterative interaction, the Writing Agent proposes structured content grounded in summarizations, while the Evaluation Agent critiques and refines these outputs to ensure coherence and balance. This cooperative setup enables the agents to jointly construct and improve survey papers by integrating both external evidence and internal reasoning. An overview of the overall generation process is provided in Algorithm 2.

**3.2.1 Structured Outline Construction.** The Writing Agent constructs an initial structured outline by grounding each section and subsection in the  $K + N$  multi-aspect summarizations, ensuring both factual grounding and thematic coherence. The Evaluation Agent then reviews the draft, assessing logical flow and suggesting refinements without altering the overall structure. After one or two feedback iterations, the outline converges into a coherent and evidence-supported framework. Detailed prompting for both agents is provided in Figure 5 and Appendix C. The key innovation of SurveyG lies in its ability to manage long-context survey synthesis without concatenating all reference texts [9, 15] or relying on pre-existing human-written surveys [20]. Instead, it leverages hierarchical summarization from the citation graph  $G$  as structured knowledge injected into the Writing Agent.

**3.2.2 Full Paper Completion.** In the writing stage, the *Writing Agent* expands each subsection based on the structured outline and its memory, utilizing grounded summaries to ensure factual consistency and contextual relevance. Meanwhile, the *Evaluation Agent* provides critical feedback by offering broader perspectives

#### Algorithm 2 SurveyG Automated Survey Generation

```

1: Input: Survey Topic  $Q$ , Paper Database  $D$ , Max iterations  $T_{\max}$ , Summarizations  $\{T_1, \dots, T_{K+N}\}$ 
2: Output: Survey Paper  $F$ 
3: // Initialization
4: Create Writing Agent (WA) and Evaluation Agent (EA)
5: Initialize memory  $M$  for WA with  $\{T_1, \dots, T_{K+N}\}$ 
6: // Phase 1: Create Outline
7: WA generates initial outline  $O^{(0)}$  from  $M$ 
8: for  $t = 1$  to  $T_{\max}$  do
9:    $O^{(t)} = \text{WA}(M, \text{EA}(O^{(t-1)}))$ 
10:  if quality threshold met then break
11:  end if
12: end for
13:  $O^* \leftarrow O^{(t)}$ 
14: // Phase 2: Write Full Paper
15: for all subsection  $O_i \in O^*$  do
16:   WA produces an initial draft  $O_i^{(0)}$ 
17:   Refine with EA's feedback and suggested queries  $Q$ :
18:   for  $t = 1$  to  $T_{\max}$  do
19:      $O_i^{(t)} = \text{WA}(M \cup R_i^{(t)}, \text{EA}(O_i^{(t-1)}))$ 
20:     where  $R_i^{(t)} = \text{RETRIEVE}(Q_i^{(t)}, D)$ 
21:     if quality threshold met then break
22:     end if
23:   end for
24: end for
25: // Phase 3: Assemble Survey
26:  $F \leftarrow \bigcup_i O_i^{(t)}$ 
27: return  $F$ 

```

Create a comprehensive literature review outline based on the following taxonomy summaries for three layers (Foundation, Development, Frontier) and vertical directions.

**Horizontal summary:** {summary\_layer}.

**Vertical direction:** {summary\_path}.

Based on the above information, create a detailed outline for a literature review paper, organizing it into sections and subsections. **Respond with the outline in JSON format with keys:**

['section\_outline', 'subsection\_focus', 'proof\_ids'].

For each section: Put section and subsection titles in 'section\_outline'; Add a paragraph in 'subsection\_focus' describing the main focus of each subsection; Add 'proof\_ids' from either taxonomy layer or vertical direction.

Figure 5: Structured outline creation short version prompt.

and generating targeted retrieval queries to identify additional relevant papers from the database  $D$ . This iterative collaboration ensures that the final text is coherent, comprehensive, and rigorously supported by the literature. The key novelty lies in combining RAG-based retrieval, guided by the Evaluation Agent's global perspective,

with pre-built hierarchical summaries that serve as localized knowledge, enabling the generation of well-balanced and contextually rich subsections.

## 4 Experiments

### 4.1 Experimental Setup

**4.1.1 Baselines.** We compare **SurveyG** with three state-of-the-art systems. **AutoSurvey** [15] and **SurveyX** [9] represent multi-stage frameworks for automated survey generation, with SurveyX enhancing AutoSurvey through structured knowledge extraction and outline optimization. **SurveyForge** [20], in contrast, leverages human-written survey papers from related domains as prior knowledge for heuristic outline generation, guided by a memory-driven scholar navigation agent that retrieves high-quality references for composing new surveys.

**4.1.2 Dataset Evaluation.** To assess the generalizability and robustness of **SurveyG**, we evaluate it on ten diverse computer science topics from the SurGE benchmark [10], which includes 205 ground-truth surveys and over one million papers. We recruited 20 domain experts, CS Ph.D. students from QS 5-star universities and senior AI research engineers, to curate high-quality reference papers and select one representative ground-truth survey per topic. The same experts also served as human evaluators, assessing the coherence, coverage, and factual accuracy of generated surveys. Additional details on ground-truth construction and evaluation protocols are provided in Appendix B.

**4.1.3 Implementation Details.** For fair comparison, we strictly follow the experimental settings of prior works [9, 15, 20]. Specifically, we retrieve 1,500 candidate papers for outline generation and 60 relevant papers for each chapter-writing stage, identical to SurveyForge [20]. All experiments use *GPT-4o-mini-2024-07-18* as the backbone model for both Writing and Evaluation Agents, consistent with previous studies. We generate surveys for ten predefined topics, each with ten independent trials (100 surveys in total), and report averaged results for stability. To assess cross-model robustness, we additionally test *Gemini-2.5-Flash*. For evaluation, advanced LLM judges: *GPT-4o-2024-08-06*, *Claude-3.5-Sonnet-20241022*, *DeepSeek-V3.2-Exp*, and *Gemini-2.5-Pro* are used to score both outlines and full survey texts. We set the iteration number  $T_{MAX}$  to 2, the same as AutoSurvey and SurveyForge.

**4.1.4 Evaluation Metrics.** We evaluate the generated outputs along three dimensions: outline, content, and citation quality. For **Outline Quality**, we follow the evaluation protocol of [20], using the same prompt. For content quality, we adopt the five widely used metrics from prior benchmarks [9, 10, 15, 20]: **Coverage**, **Structure**, **Relevance**, **Synthesis**, and **Critical Analysis**. Six metrics are rated on a 0-100 scale by both LLM and human judges, measuring completeness, organization, topical alignment, integrative reasoning, and analytical depth. For citation quality [5, 15], we evaluate the factual consistency between claims and their cited references using a Natural Language Inference model, reporting **Citation Recall** (ratio of supported claims), **Citation Precision** (ratio of valid references), and **Citation F1** as their harmonic mean. Details of these metrics are provided in Appendix B.

### 4.2 Evaluation on Content Quality

As shown in Table 1, **SurveyG** consistently achieves the highest scores across nearly all metrics and evaluation models, demonstrating strong generalization and robustness under different LLM judges. In particular, **SurveyG** shows notable gains in **Synthesis** and **Critical Analysis**, reflecting its ability to integrate information and identify research gaps through the use of a hierarchical citation graph and multi-level summarization prompts. **SurveyForge** ranks second overall, outperforming **SurveyX** and **AutoSurvey** in **Coverage** and **Structure** due to its heuristic use of human-written surveys as prior knowledge. However, it remains less effective than **SurveyG**, which achieves superior organization and analytical depth without relying on human-written inputs, instead leveraging structured summarization and cross-community reasoning within the hierarchical framework.

### 4.3 Evaluation on Ground Truth

Figure 6 reveals distinct performance patterns among the three approaches. In Synthesis, SurveyG achieves the most balanced performance, closely matching human surveys and showing more consistent scores than SurveyForge across metrics like OOD Detection and Hallucination in LLM. For Coverage, while human surveys lead with 90 scores, SurveyG demonstrates more stable cross-topic performance compared to SurveyForge’s variable results, particularly in specialized areas like Knowledge Graph Embedding and RL for Language Processing. In Critical Analysis, both automated methods score 70-85, but SurveyG shows less variation between metrics, indicating more reliable quality. Overall, while SurveyForge occasionally peaks higher in individual metrics, SurveyG’s consistently uniform polygon shapes across all three dimensions suggest superior robustness and generalization capability for diverse survey generation tasks.

### 4.4 Evaluation on Citation Quality

The experimental results presented in Table 2 clearly indicate that the SurveyG (ours) model sets a new standard for automated survey generation, demonstrating superior citation quality compared to existing systems. SurveyG achieves the highest Recall at 90.60 and the best F1 Score at 83.49. This high Recall figure is particularly notable, as it is very close to the Ground Truth Recall of 92.53, suggesting SurveyG is highly effective at comprehensively identifying and linking relevant literature. While SurveyX holds the lead in Precision (78.12), SurveyG’s significantly better F1 Score confirms its overall advantage in balancing the inclusion of necessary citations with the exclusion of irrelevant ones. In summary, SurveyG (ours) surpasses AutoSurvey, SurveyForge, and SurveyX in overall performance, demonstrating a marked improvement in the reliability and comprehensiveness of citations in generated surveys.

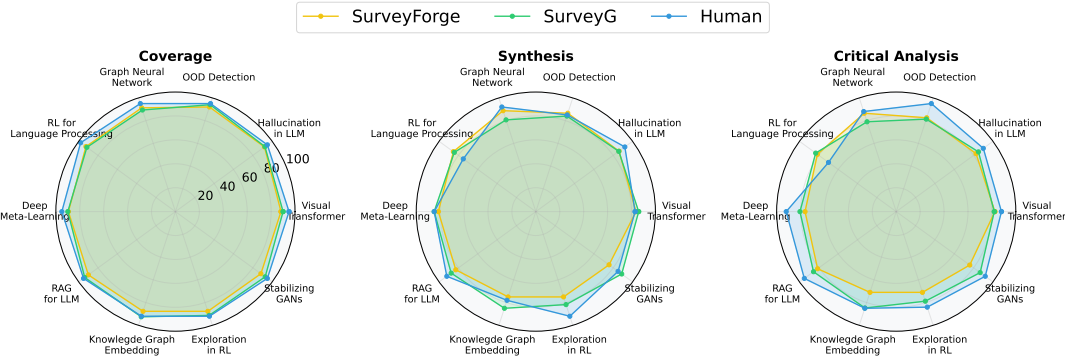
### 4.5 Human Evaluation

To validate our automated evaluation framework, we conducted a comparative assessment between **SurveyG** (ours) and **SurveyForge** across ten topics. We adopted a win-rate-based evaluation protocol, presenting anonymized outputs from both systems to domain experts and the automated evaluation system. Human experts were selected based on topic relevance and possessed extensive



LLM	Model	Coverage	Structure	Relevance	Synthesis	Critical Analysis
<b>Claude</b>	AutoSurvey	73.6	64.5	80.2	51.1	45.8
	SurveyForge	81.8	78.4	89.1	75.4	70.3
	SurveyX	74.2	71.3	82.3	62.4	52.7
	SurveyG	<b>88.1</b>	<b>87.9</b>	<b>93.6</b>	<b>80.2</b>	<b>77.3</b>
<b>GPT</b>	AutoSurvey	90.7	86.2	89.3	84.6	82.3
	SurveyForge	94.2	87.3	94.8	88.6	88.5
	SurveyX	89.3	84.4	88.5	79.2	78.4
	SurveyG	<b>95.7</b>	<b>88.5</b>	<b>95.1</b>	<b>92.2</b>	<b>90.5</b>
<b>Deepseek</b>	AutoSurvey	86.5	80.4	87.8	77.3	72.4
	SurveyForge	<b>89.4</b>	<b>86.5</b>	92.5	84.1	80.7
	SurveyX	85.4	81.2	89.4	78.2	75.6
	SurveyG	88.7	82.7	<b>93.4</b>	<b>85.5</b>	<b>81.6</b>
<b>Gemini</b>	AutoSurvey	94.2	70.8	96.5	83.6	84.2
	SurveyForge	94.9	<b>93.1</b>	<b>98.7</b>	93.5	94.2
	SurveyX	90.2	71.2	95.6	82.8	84.5
	SurveyG	<b>96.2</b>	89.4	97.6	<b>93.6</b>	<b>94.9</b>

**Table 1: LLM-as-a-judge evaluation of generated surveys. Each LLM evaluates four generation models across content quality dimensions.**



**Figure 6: LLM-as-a-judge evaluation of human-written ground-truth surveys, SurveyForge, and SurveyG across ten topics using GPT-4o as the evaluator.**

Model	Recall	Precision	F1 Score
AutoSurvey	82.25	77.41	79.76
SurveyForge	88.34	75.92	81.66
SurveyX	85.23	<b>78.12</b>	81.52
SurveyG (ours)	<b>90.60</b>	76.32	<b>83.49</b>
Ground Truth	92.53	86.42	89.34

**Table 2: Performance comparison of different models on citation quality metrics.**

research experience in their respective domains. As summarized in Table 3, three complementary metrics were used to quantify performance differences. The *Score Win Rate* measures how often a model receives a higher absolute score from the LLM evaluator. The *Comparative Win Rate* reflects the frequency with which the LLM selects a model’s paper as superior in pairwise comparisons. The *Human Evaluation Win Rate* represents the proportion of times

human experts preferred outputs from one model over the other. Under this framework, **SurveyG** consistently outperforms **SurveyForge**, achieving a *Score Win Rate* of 61.15%, a *Comparative Win Rate* of 72.25%, a *Human Evaluation Win Rate* of 64.00%, and an overall score of 87.67%. In contrast, **SurveyForge** records 38.85%, 27.75%, 36.00%, and 82.55%, respectively. These results demonstrate strong consistency between automated and human evaluations, confirming that our framework reliably captures expert-level judgment while maintaining scalability and efficiency.

As shown in Table 4, three complementary metrics were adopted to evaluate model performance on outline generation. Under this evaluation framework, SurveyG (ours) consistently outperforms SurveyForge, achieving a *Score Win Rate* of 55.00%, a *Comparative Win Rate* of 58.00%, a *Human Evaluation score* of 55.00%, and an *Overall Score* of 95.00%. In contrast, SurveyForge records 45.00%, 42.00%, 45.00%, and 90.00%, respectively. These findings demonstrate that our model produces higher-quality outlines, confirming

Model	Score Win Rate	Comparative Win Rate	Human Eval	Overall Score
SurveyForge	<b>38.85%</b>	27.75%	<b>36.00%</b>	<b>82.55%</b>
SurveyG (ours)	<b>61.15%</b>	72.25%	<b>64.00%</b>	<b>87.67%</b>

**Table 3: Comparison of models across full paper evaluation metrics.**

Model	Score Win Rate	Comparative Win Rate	Human Eval	Overall Score
SurveyForge	<b>45.00%</b>	<b>42.00%</b>	<b>45.00%</b>	<b>90.00%</b>
SurveyG (ours)	<b>55.00%</b>	<b>58.00%</b>	<b>55.00%</b>	<b>95.00%</b>

**Table 4: Comparison of models based on outline evaluation metrics.**

that constructing a Hierarchical Citation Graph for paper retrieval in outline generation is a principled and effective approach.

**4.5.1 Details of Human Evaluation.** To evaluate reliability, we assigned two domain experts to each of the ten SurGE topics. For every topic, we randomly sampled ten anonymized outputs from **SurveyG** and ten from **SurveyForge**, each obtained from independent generation runs. All outputs were fully anonymized, ensuring that neither the human experts nor the LLM judge (*GPT-4o*) was aware of their system of origin. Both experts independently rated all 20 outputs per topic using identical evaluation prompts and criteria, which covered five content metrics **Structure**, **Coverage**, **Relevance**, **Synthesis**, and **Critical Analysis** as well as an outline quality score (0 to 100). For each topic, we computed Cohen’s  $\kappa$  to measure (i) agreement between the LLM and human raters, and (ii) agreement between human raters. Table 7 reports topic-wise and average  $\kappa$  values. The mean Cohen’s  $\kappa$  for the outline metric was 0.6972 (LLM-human) versus 0.7542 (human-human), and for content metrics, 0.6062 versus 0.7127, respectively. These results demonstrate substantial inter-rater reliability and confirm that the LLM-as-a-judge evaluations align closely with expert assessments.

Evaluation Pair	Aspect	Cohen $\kappa$
LLM vs. Human	Outline	0.6972
LLM vs. Human	Content	0.6062
Human Cross-Validation	Outline	0.7542
Human Cross-Validation	Content	0.7127

**Table 5: Inter-rater agreement between LLM and human evaluations**

## 4.6 Cost estimation

The SurveyG framework generates survey papers with an average length of approximately 64k tokens, comparable to expert-written surveys. Each subsection is produced using around 12k input tokens and 800 output tokens. Additionally, the Evaluation Agent in the RAG loop performs one assessment per subsection, consuming approximately 3.7k input and 700 output tokens. Using this configuration, the total cost for generating a full 64k-token survey is estimated at \$1.5-\$1.7, depending on model pricing and API parameters. These results highlight the cost-effectiveness and scalability

Variant	Cov.	Str.	Rel.	Syn.	C.A
<b>Full</b>	<b>91.98</b>	<b>86.78</b>	<b>94.81</b>	<b>85.44</b>	<b>83.34</b>
w/o Vertical Traversal	90.51	85.05	93.91	84.92	84.28
w/o Horizontal Clustering	91.80	86.22	94.61	83.91	86.01
w/o MA	89.26	84.36	91.50	83.73	81.43

**Table 6: We test three variants: (1) w/o Vertical Traversal uses only horizontal clustering and summarization within each layer; (2) w/o Horizontal Clustering performs only vertical path traversal from foundation papers; (3) w/o MA removes the Multi-Agent component.**

of the SurveyG framework for producing high-quality, large-scale literature surveys.

## 4.7 Ablation Studies

In Table 6, to evaluate the contribution of each component in our architecture, we present ablation study results comparing our full model against variants with specific components removed. Our full version achieves the best overall performance, demonstrating the effectiveness of our complete architecture. The inclusion of RAG significantly enhances Coverage (91.98) and Relevance (94.81) compared to the w/o MA variant (89.26 and 91.50), as it supplements the model with additional contextual information. More importantly, the full model outperforms both the w/o Vertical Traversal and w/o Horizontal Clustering variants, particularly in Structure scores (86.78), indicating that having all components working together enables superior information synthesis. This complete architecture allows the model to effectively integrate and organize information from multiple sources, resulting in more coherent and well-structured outputs across all evaluation metrics.

## 5 Conclusion

In this work, we introduced SurveyG, an automated framework for survey generation that leverages hierarchical knowledge representation and multi-agent collaboration to address the limitations of existing LLM-based approaches. By modeling papers through a three-layer citation-similarity graph and employing both horizontal and vertical traversal strategies, SurveyG captures the structural relationships and evolutionary progress of research, enabling the creation of coherent and well-structured outlines. Through



extensive evaluations, we demonstrated the effectiveness of our framework across diverse computer science topics. On the SurGE benchmark for autonomous computer science survey generation, both LLM-as-a-judge evaluations and human expert assessments demonstrate that SurveyG outperforms state-of-the-art frameworks across multiple dimensions.

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### Algorithm 3 Weighted Breadth-First Search (WBFS)

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```

1: Input: Start node  $s$ , target layer  $\ell$ 
2: Output: Set of nodes  $R$  in layer  $\ell$ 
3:  $visited \leftarrow \{s\}$ ,  $queue \leftarrow [s]$ ,  $R \leftarrow \emptyset$ 
4: while  $queue \neq \emptyset$  do
5:    $u \leftarrow queue.DEQUEUE()$ 
6:   for all  $v \in \text{SUCCESSORS}(u)$  sorted by  $weight(u, v)$  desc do
7:     if  $v \notin visited$  then
8:        $visited \leftarrow visited \cup \{v\}$ 
9:       if  $v.layer = \ell$  then
10:         $R \leftarrow R \cup \{v\}$ 
11:       else
12:         $queue.ENQUEUE(v)$ 
13:     end if
14:   end if
15: end for
16: end while
17: return  $R$ 

```

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## A Details about Traversal on Graph

We provide a full algorithm of Weighted BFS in Algorithm 3.

## B Experimental Setting

### B.1 Survey Topics

We compiled a collection of ten representative survey papers covering diverse research areas, as summarized in Table 7. Each topic reflects an active line of inquiry within machine learning and natural language processing, providing a strong foundation for evaluating literature review generation.

### B.2 Evaluation Metrics

**B.2.1 Metrics about Content Quality.** We evaluate both the quality of the generated outlines and the full survey papers. A well-structured and logically coherent outline is essential for maintaining clarity and organization, and we adopt the same evaluation settings as in [20]. The full paper evaluation serves as a comprehensive qualitative benchmark to assess the academic rigor and practical utility of the generated surveys. Following the prompt design and evaluation protocols from previous studies [9, 10, 15, 20], we assess survey quality across five key metrics: **Coverage**, which measures how thoroughly the survey captures major concepts, foundational works, and emerging trends; **Structure**, which examines logical organization, coherence, and taxonomy quality; **Relevance**, which assesses the alignment of content with the target research topic; **Synthesis**, which evaluates the integration of information from multiple sources into a cohesive and non-redundant narrative; and **Critical Analysis**, which reflects the survey’s ability to identify methodological gaps, highlight trends, and articulate open research

Topic	Ground Truth Survey	Citation
Visual Transformer	A Survey of Visual Transformers	405
Hallucination in Large Language Models	Siren’s Song in the AI Ocean: A Survey on Hallucination in LLMs	808
Graph Neural Networks	Graph Neural Networks: Taxonomy, Advances, and Trends	129
Deep Meta-Learning	A Survey of Deep Meta-Learning	459
Knowledge Graph Embedding	Knowledge graph embedding: A survey from the perspective of representation spaces	130
Generalized Out-of-Distribution Detection	Generalized Out-of-Distribution Detection: A Survey	1406
Reinforcement Learning for Language Processing	Survey on reinforcement learning for language processing	206
Exploration Methods in Reinforcement Learning	Exploration in Deep Reinforcement Learning: From Single-Agent to Multi-Agent Domain	194
Stabilizing Generative Adversarial Networks	Stabilizing Generative Adversarial Networks: A Survey	149
Retrieval-Augmented Generation for LLMs	Retrieval-Augmented Generation for Large Language Models: A Survey	953

Table 7: Survey Papers Overview

challenges. Each metric is scored on a 0–100 scale by both LLM-based judges and human experts, with higher scores indicating stronger performance. The complete evaluation prompts and scoring criteria are detailed in Appendix B.

**B.2.2 Metric about Citation Quality.** Following the methodology in prior studies [5, 15], we evaluate the citation quality of the generated surveys by measuring both the accuracy and the contextual relevance of cited references. Specifically, we extract a set of factual claims from each generated survey and verify whether these claims are appropriately supported by their corresponding references. To automate this process, we employ a Natural Language Inference (NLI) model that determines whether the content of each cited paper logically supports the associated claim. Based on this evaluation, we calculate two key metrics: **Citation Recall**, which reflects the proportion of claims that are correctly supported by valid references, and **Citation Precision**, which measures the proportion of cited references that truly substantiate the claims they are linked to. Together, these metrics provide a robust measure of how accurately and meaningfully the generated surveys integrate citations within their arguments.

## C Prompt Templates

This section presents the prompt templates designed to guide each stage of automated literature review generation and evaluation. Each template specifies goals, inputs, and evaluation criteria to ensure consistency and quality across generated outputs.

### C.1 Prompt to generate structured outline

We provide a short version of the prompt template (Figure 7) that instructs the model to construct a coherent, hierarchical outline that captures the logical flow of a literature review topic before detailed writing begins.

### C.2 Prompt to evaluate structured outline

The prompt in Figure 8 guides the model to write complete, citation-based literature review subsections grounded in the provided focus, summaries, and development directions. The following evaluation prompt extends this process to assess individual sections for depth, synthesis, and analytical quality.

**Goal:** Generate a structured Literature Review Outline for: "[QUERY]"

#### INPUT SYNTHESIS DATA

- **Communities:** [PAPER\_COMMUNITIES]
- **Directions:** [DEVELOPMENT\_DIRECTIONS]

#### REQUIREMENTS & CONSTRAINTS

##### 1. Structure:

- **Progression:** Follow Foundations → Core → Advanced → Applications → Future.
- **Mandatory Sections:** Must include Introduction, Foundational Concepts, and Conclusion.
- **Hierarchy:** Use exactly **TWO levels** (e.g., 2.1, 2.2). No deeper nesting.

##### 2. Content & Quality:

- Create a **coherent narrative** (evolutionary story, not a list).
- Group material by **methodological families** and thematic depth.
- Include dedicated sections for Applications and Future Trends/Challenges.

##### 3. Evidence & Output:

- **Proof IDs:** Each subsection **MUST** be grounded with 1-3 proof\_ids (from layer, community\_X, or seed IDs).
- **Focus Synthesis:** Provide section\_focus (broad theme) and subsection\_focus (specific details).
- **Format:** Return only a **JSON ARRAY** of main sections and their hierarchical subsections.

Figure 7: Generate Outline Prompt.

### C.3 Prompt to generate subsections

This prompt guides the model to write complete, citation-based literature review subsections grounded in the provided focus, summaries, and development directions (Figure 9).

Evaluate the quality and structure of the following literature review outline. Assess whether the outline demonstrates meaningful organization of works rather than a simple concatenation of summaries. **Your feedback should include:**

- Strengths of the outline.
- Weaknesses or issues (if any).
- Specific suggestions for improvement (only if issues are found).
- Final score (1-5, with 5 being the maximum) evaluate overall organization, coherence, and coverage.

Outline to evaluate: {outline\_text}

Figure 8: Prompt to evaluate structured outline

Evaluate the quality of the following literature review section within the context of the overall survey outline. Your evaluation should address the following aspects, each rated from 1-5 (5 = excellent): (1) content coverage, (2) citation density, (3) academic rigor, (4) synthesis across works, (5) critical analysis, (6) coherence, (7) depth of discussion, and (8) specificity of scope.

In addition to numeric ratings, provide:

- A brief natural language summary of the section's strengths and weaknesses,
- An overall score (1-5) with justification,
- Suggestions for improvement, focusing on areas that fall short,
- A list of search queries that could retrieve additional relevant literature to strengthen the section.

Figure 10: Section Quality and Retrieval Prompt

**Task:** Write a comprehensive literature review subsection titled [SUBSECTION\_TITLE] in LaTeX.

**Inputs:**

- **Focus:** [SUBSECTION\_FOCUS]
- **Community summaries:** [COMMUNITY\_SUMMARY]
- **Development directions:** [DEVELOPMENT\_DIRECTION]
- **Papers (chronological):** [PAPER\_INFO]

**Guidelines:**

- Use LaTeX format with citations (`\cite{citation_key}`).
- Minimum 400 words, no numbered subsection titles.
- Focus strictly on the subsection topic.
- Each paper: 2-3 sentences describing technical contributions.
- Connect papers by showing how later work addresses earlier limitations.
- Conclude with remaining challenges or future directions.

**Avoid:** sequential listing, vague critiques, unsupported claims, isolated descriptions, or ignoring contradictions.

Figure 9: Generate Subsection Prompt Short Version

## D Case studies

We provided a subsection generated by **SurveyG** (Figure 11) to illustrate its ability to synthesize complex research trends in modular and agentic RAG. Overall, this subsection highlights a clear progression in the RAG landscape from simple retrieval pipelines toward multi-stage, agentic, and modular architectures. The discussed works collectively show how LLMs are evolving from passive generators to proactive reasoning agents capable of planning, coordination, and self-optimization. The emergence of meta-frameworks such as AutoRAG and FlashRAG further reflects a shift toward automated orchestration of RAG components, underscoring a broader trend toward unified, adaptive systems that integrate retrieval and reasoning for scalable knowledge synthesis.

## C.4 Improve Section Quality

As shown in Figure 10, this prompt systematically assesses literature review sections across multiple dimensions such as content coverage, synthesis, and critical analysis while offering actionable feedback and retrieval suggestions for refinement.

### Multi-stage and Modular RAG Frameworks

The foundational paradigm of Retrieval-Augmented Generation (RAG) typically operates on a straightforward "retrieve-then-generate" sequence [lewis2020pwr]. However, as Large Language Models (LLMs) are increasingly tasked with complex, multi-faceted queries and dynamic information needs, this simple pipeline proves insufficient [huang2024a59, zhao2024931]. This has spurred the evolution of RAG into more sophisticated, multi-stage, and modular architectures, where the LLM transcends a passive role to become an intelligent agent capable of proactive planning, dynamic decision-making, and the orchestration of various sub-tasks [gao20238ea]. This section focuses on frameworks that empower LLMs to actively manage the information-seeking process through iterative planning, query decomposition, and the dynamic assembly of specialized modules. It is crucial to distinguish these proactive, agentic approaches from reactive or corrective mechanisms (e.g., self-correction, re-ranking) that primarily refine retrieval quality, which are discussed in detail in Section 3.

A significant advancement in modular RAG involves empowering LLMs to act as sophisticated planning agents, iteratively refining their information-seeking process and orchestrating multi-round interactions. [lee2024hif] introduced PlanRAG, which extends the popular ReAct framework by incorporating explicit "Plan" and "Re-plan" steps. This allows LLMs to dynamically generate and iteratively refine analytical approaches based on intermediate retrieval results, effectively acting as decision-makers for complex data analysis tasks. Similarly, [yang20243nb] presented IM-RAG, a multi-round RAG system that leverages learned inner monologues and a multi-agent reinforcement learning approach. In IM-RAG, an LLM-based "Reasoner" dynamically switches between a "Questioner" role (crafting queries) and an "Answerer" role, guided by mid-step rewards from a "Progress Tracker," leading to flexible and interpretable multi-round information gathering. Building on the concept of autonomous interaction, [yu2024c32]'s Auto-RAG enables LLMs to engage in multi-turn dialogues with the retriever, systematically planning retrievals and refining queries until sufficient external information is gathered. This framework highlights the LLM's powerful decision-making capabilities, autonomously adjusting iterations based on query difficulty and knowledge utility. Another approach, [wang2024zt3]'s M-RAG, proposes a multi-partition paradigm for external memories, employing a multi-agent reinforcement learning framework with an "Agent-S" for dynamic partition selection and an "Agent-R" for memory refinement. This enables more fine-grained and focused retrieval by orchestrating memory access across different knowledge partitions. To further optimize the interaction between these modular components, [li20243nz]'s RAG-DDR (Differentiable Data Rewards) offers an end-to-end training method that aligns data preferences between different RAG modules (agents). By collecting rewards and evaluating the impact of perturbations on the entire system, RAG-DDR optimizes agents to produce outputs that enhance overall RAG performance, particularly for smaller LLMs. These agentic frameworks collectively transform RAG into a dynamic, adaptive system capable of tackling complex, multi-hop queries that require sophisticated reasoning and iterative information synthesis.

...

In conclusion, the evolution towards multi-stage and modular RAG frameworks marks a significant advancement, transforming RAG from a simple pipeline into an intelligent, adaptive system. By enabling LLMs to engage in iterative refinement, agentic planning, and dynamic orchestration of sub-tasks, these architectures enhance robustness, reduce hallucinations, and improve the depth and faithfulness of generated responses, particularly for complex, multi-hop queries [tang2024i5r]. However, this sophistication often introduces challenges related to increased computational overhead, the complexity of orchestrating multiple modules, and the need for robust evaluation methodologies that can accurately assess the contributions of each stage and the overall system performance. Benchmarks like [friel20241ct]'s RAGBench, [krishna2024qsh]'s FRAMES, and [tang2024i5r]'s MultiHop-RAG highlight these challenges, emphasizing the need for explainable metrics and unified frameworks to evaluate the intricate interplay of retrieval, reasoning, and generation in these advanced systems. Future research will likely focus on optimizing the efficiency of these multi-stage processes, developing more autonomous and self-correcting agents, and creating more generalized frameworks that can seamlessly integrate diverse knowledge sources and reasoning paradigms while addressing the inherent trade-offs between complexity and efficiency.

**Figure 11: Case studies about the result of generated subsection.**