Scaling Beyond Context: A Survey of Multimodal Retrieval-Augmented Generation for Document Understanding

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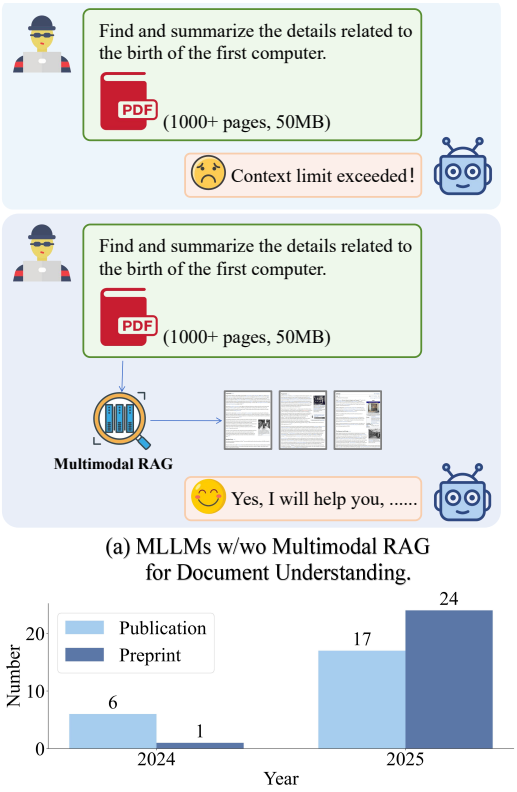
Abstract

Document understanding is critical for applications from financial analysis to scientific discovery. Current approaches, whether OCR-based pipelines feeding Large Language Models (LLMs) or native Multimodal LLMs (MLLMs), face key limitations: the former loses structural detail, while the latter struggles with context modeling. Retrieval-Augmented Generation (RAG) helps ground models in external data, but documents' multimodal nature, *i.e.*, combining text, tables, charts, and layout, demands a more advanced paradigm: Multimodal RAG. This approach enables holistic retrieval and reasoning across all modalities, unlocking comprehensive document intelligence. Recognizing its importance, this paper presents a systematic survey of Multimodal RAG for document understanding. We propose a taxonomy based on domain, retrieval modality, and granularity, and review advances involving graph structures and agentic frameworks. We also summarize key datasets, benchmarks, applications and industry deployment, and highlight open challenges in efficiency, fine-grained representation, and robustness, providing a roadmap for future progress in document AI.



(a) MLLMs w/wo Multimodal RAG for Document Understanding.

(b) Number of Papers on Multimodal RAG for Document Understanding.

Figure 1: **Impact and research progress of Multimodal RAG for document understanding:** (a) MLLMs with and without Multimodal RAG for large document comprehension. (b) Growth in related publications from 2024 to 2025.

1 Introduction

Document understanding has become a pivotal task in the era of information explosion, as it empowers machines to automatically interpret, organize, and reason over the massive volumes of unstructured and semi-structured documents produced across diverse domains (Subramani et al., 2020; Ding et al., 2024). Early studies primarily focus on text-centric documents, relying on optical character recognition (OCR) techniques (Gu et al., 2021; Appalaraju et al., 2021; Shi et al., 2016) to support layout analysis and key information extraction. However, in real-world scenarios, particularly in scientific domains, documents are often visually rich and contain complex elements such as tables, charts, and images (Park et al., 2019; Ding et al., 2025a). With the rapid progress of Large Language Models (LLMs) and the rising demand for understanding increasingly complex and diverse document types, developing robust and generalizable document understanding frameworks has become an area of growing interest.

In visually rich document understanding, different approaches have emerged to address the challenges of integrating layout, text, and structural information. Multimodal LLM (MLLM)-native methods commonly represent documents as long

Benchmark	Scope	# Pages	Visual Tokens
M3DocVQA (Cho et al., 2024a)	Open-Domain	∼40K	∼41M
VisDoMBench (Suri et al., 2025)	Open-Domain	∼21K	∼21M
OpenDocVQA (Tanaka et al., 2025)	Open-Domain	∼206K	∼206M

Table 1: Scale of representative document RAG benchmarks. Visual tokens are estimated assuming ∼1K visual tokens per page.

image sequences, enabling unified learning across modalities with MLLMs (Duan et al., 2025; Xiong et al., 2025; Yu et al., 2025c; Zhou et al., 2024; Nassar et al., 2025; Ye et al., 2023; Hu et al., 2024a,b). While effective, these models struggle with very long documents spanning hundreds or thousands of pages, where sequence length limitations can hinder accurate retrieval and increase the risk of hallucination (Deng et al., 2024a; Ma et al., 2024c). As shown in Table 1, current multimodal RAG benchmarks require 20–200M visual tokens, far exceeding the typical 128K–1M context limits of existing MLLMs (Yang et al., 2025; Achiam et al., 2023; Team et al., 2023). To improve modularity and robustness, agent-based approaches introduce specialized agents for subtasks such as layout analysis, content extraction, instruction decomposition, and verification (Liu et al., 2025b; Han et al., 2025; Wang et al., 2025a; Wu et al.; Yu et al., 2025d), though such designs often increase system complexity due to coordination overhead. Retrieval-augmented generation (RAG) methods provide another direction by grounding responses with external knowledge, typically retrieving the top-K most relevant pages (see Figure 1 (a)) across one or more documents (Lewis et al., 2020). Importantly, these paradigms are not mutually exclusive: RAG-based systems may employ agents to manage retrieval and verification, while agent-based workflows often incorporate RAG as one of the agent nodes, yielding more flexible hybrid frameworks. These complementary perspectives have shaped the landscape of document understanding, yet among them, RAG has drawn particular attention for its practicality and rapid growth (Arslan et al., 2024; Fan et al., 2024).

Early RAG studies mainly rely on text-centric strategies, extracting text via OCR or combining OCR with MLLM-generated captions for visually rich documents, followed by encoding for retrieval (Wang et al., 2022; Li et al., 2023; Chen et al., 2024c; Khattab and Zaharia, 2020). Despite their effectiveness in certain scenarios, such text-based approaches exhibit fundamental limitations in handling visually rich documents, as they fail to adequately capture cross-modal cues and structural semantics (Abootorabi et al., 2025; Mei et al., 2025). To address these shortcomings, recent efforts have increasingly focused on multimodal RAG frameworks. The growth trend in the number of papers is shown in Figure 1 (b). These methods often represent multi-page documents as image sequences (Faysse et al., 2024; Yu et al., 2024), enabling visual encoders to extract richer representations for retrieval. Recent advances in multimodal RAG have increasingly emphasized finer-grained modeling within individual pages, including tables, charts, and other structured elements, to improve retrieval accuracy and robustness (Wang et al., 2025c; Choi et al., 2025). Extending beyond these coarse-to-fine refinements, recent studies have also investigated graph-based indexing (Yuan et al., 2025) and multi-agent frameworks (Liu et al., 2025b), which provide complementary mechanisms for structured reasoning and collaborative coordination in multimodal RAG.

This rapid evolution and increasing complexity in the field have naturally prompted efforts to synthesize the existing literature. However, a closer look reveals a significant gap. Prior surveys have reviewed RAG from multiple perspectives (Arslan et al., 2024; Fan et al., 2024; Gao et al., 2023; Hu and Lu, 2024; Gupta et al., 2024; Zhao et al., 2024; Church et al., 2024). In parallel, recent surveys examining multimodal RAG (Zhao et al., 2023; Abootorabi et al., 2025; Mei et al., 2025) offer limited coverage of document understanding, typically discussing only a few relevant methods. Conversely, while document understanding has been extensively reviewed (Subramani et al., 2020; Ding et al., 2024; Nandi and Sathya, 2024; Van Landeghem et al., 2023; Ding et al., 2025b), existing surveys rarely address multimodal RAG. To bridge this gap, we present the first comprehensive survey that explicitly connects multimodal RAG and document understanding. Unlike prior works that emphasize one aspect while overlooking the other, our survey systematically analyzes their intersection and organizes the most extensive collection of studies in this emerging field. Our contributions can be summarized as follows: (1) We present a comprehensive survey that categorizes existing methods by domain, retrieval modality, granularity, and hybrid enhancements, offering a structured perspective for future research. (2) We compile a broad collection of multimodal RAG datasets, benchmarks, and comparative results for systematic evaluation, and survey evaluation metrics spanning both retrieval

and generation. Together, these contributions outline a coherent landscape of multimodal RAG for document understanding, providing both a reference and guidance for future progress.

2 Preliminary

In RAG, a system retrieves a set of relevant document pages and then generates a response conditioned on that evidence. Retrieval can be *closed-domain* (*e.g.*, grounding to a single source document) or *open-domain* (searching a large corpus). We denote the candidate pool by $D = \{d_i\}_{i=1}^{N}$. Each d_i may include a raster image as well as OCR text T_i. Using modality-specific encoders, we map queries and documents into a shared embedding space. Our notation uses lower-case symbols with subscripts for vectors (*e.g.*, z_i, e_q), and we compute similarity using inner products. Typically, the query q is text, so we compute both text–text and text–image similarities in this shared space (and, if q includes images, e_q^{img} can be defined analogously).

To embed documents and queries, we use image and text encoders: $z_i^{\text{img}} = \text{Enc}_{\text{img}}(d_i)$, $z_i^{\text{text}} = \text{Enc}_{\text{text}}(T_i)$, and $e_q^{\text{text}} = \text{Enc}_{\text{text}}(q)$. Within each modality pair, similarities are inner products (optionally with unit-norm embeddings so the score is cosine similarity): $s_{\text{text}}(e_q, z_i) = \langle e_q^{\text{text}}, z_i^{\text{text}} \rangle$ and $s_{\text{img}}(e_q, z_i) = \langle e_q^{\text{text}}, z_i^{\text{img}} \rangle$.

Vision-only retrieval. When using only the image channel (*i.e.*, for text-image similarity), we rank documents with the score $s_{\text{img}}(e_q, z_i)$ and select those that exceed a threshold τ_{img} (or simply take the K results):

$$X_{\text{img}} = \{\, d_i \in D \mid s_{\text{img}}(e_q, z_i) \geq \tau_{\text{img}} \,\}. \quad (1)$$

Joint vision–text retrieval. We consider two widely used strategies.

(a) Confidence-weighted score fusion. Image and text scores are combined with a convex weight that reflects per-item or per-query confidence. Let $\lambda_i \in [0, 1]$ denote the image confidence for d_i (*e.g.*, from calibration or OCR quality); setting λ_i=1 recovers vision-only and λ_i=0 text-only:

$$\begin{aligned} s_{\text{conf}}(e_q, z_i) &= \lambda_i \, s_{\text{img}}(e_q, z_i) \\ &\quad + (1 - \lambda_i) \, s_{\text{text}}(e_q, z_i), \\ X_{\text{conf}} &= \{\, d_i \in D \mid s_{\text{conf}}(e_q, z_i) \geq \tau_{\text{conf}} \,\}. \end{aligned} \quad (2)$$

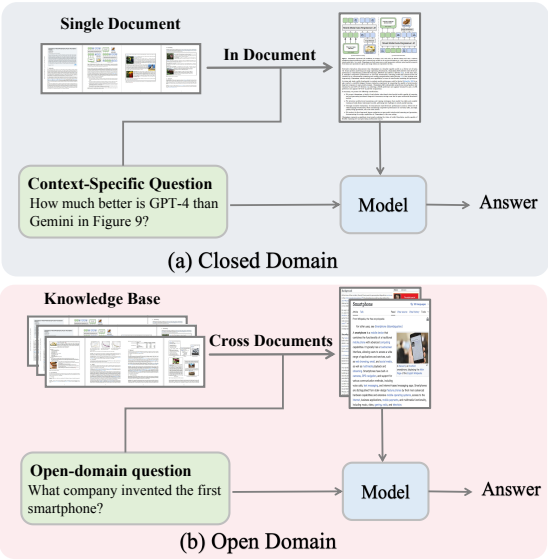


Figure 2: **Comparison between closed-domain and open-domain multimodal RAG**. (a) In the closed domain, the model leverages in-document retrieval from a single document to answer context-specific questions. (b) In the open domain, the model relies on cross-document retrieval from multiple documents to answer open-ended questions.

(b) Union of modality-specific pages. This strategy involves retrieving pages with each modality independently and then forming the union of the results (optionally followed by deduplication or rank fusion such as Borda or reciprocal-rank fusion (Cormack et al., 2009; Calumby et al., 2017)) using modality-aware thresholds $\tau_{\text{img}}, \tau_{\text{text}}$:

$$\begin{aligned} X_{\text{img}} &= \{\, d_i \in D \mid s_{\text{img}}(e_q, z_i) \geq \tau_{\text{img}} \,\}, \\ X_{\text{text}} &= \{\, d_i \in D \mid s_{\text{text}}(e_q, z_i) \geq \tau_{\text{text}} \,\}, \\ X_{\cup} &= X_{\text{img}} \cup X_{\text{text}}. \end{aligned} \quad (3)$$

(Equivalently, one may use top-K per modality and take the union $X_{\cup}^{(K)}$.)

Generation. A generator $\mathcal{G}$ conditions on the original query and the retrieved context chosen as X_{img}, X_{conf}, or $X_{\cup}$ depending on the retrieval regime and produces the final response. The specific mechanism for aggregating multiple pages (*e.g.*, via cross-attention or learned pooling) is left abstract:

$$r = \mathcal{G}(q, X). \quad (4)$$

3 Key Innovations and Methodologies

In this section, we examine the core innovations and methodological advances in recent multimodal

Method	Venue	LLM/VLM	Vision Encoder	Training	OCR	Domain	Modality	Granularity	Graph	Agent
DSE (2024b)	EMNLP	Phi3V	CLIP-ViT-L/14	✓	✗	Open	Image	Page	✗	✗
ColPali (2024)	ICLR	PaliGemma-3B	SigLIP-SO400M	✓	✗	Open	Image	Page	✗	✗
ColQwen2 (2024)	ICLR	Qwen2-VL-2B	ViT-BigG	✓	✗	Open	Image	Page	✗	✗
CREAM (2024a)	ACM MM	LLaMA2-7B	Pix2Struct	✓	✓	Closed	Image+Text	Page	✗	✗
VisRAG (2024)	ICLR	MiniCPM-V2.0	SigLIP-SO400M	✓	✗	Open	Image	Page	✗	✗
SV-RAG (2024b)	ICLR	InternVL2-4B	InternViT-300M	✓	✗	Closed	Image	Page	✗	✗
M3DocRAG (2024a)	Preprint	Qwen2-VL-7B	ViT-BigG	✗	✗	Open	Image	Page	✗	✗
VisDoMRAG (2025)	NAACL	Qwen2-VL-2B	ViT-BigG	✗	✓	Open	Image+Text	Page	✗	✗
GME (2025d)	CVPR	Qwen2-VL-7B	ViT-BigG	✓	✓	Open	Image+Text	Page	✗	✗
ViDoRAG (2025b)	EMNLP	Qwen2.5-VL-7B	ViT-BigG	✗	✓	Open	Image+Text	Page	✗	✓
HM-RAG (2025b)	ACM MM	Qwen2.5-VL-7B	ViT-BigG	✗	✓	Open	Image+Text	Page	✓	✓
VDocRAG (2025)	CVPR	Phi3V	CLIP-ViT-L/14	✓	✗	Open	Image	Page	✗	✗
FRAG (2025a)	Preprint	InternVL2-8B	InternViT-300M	✗	✗	Closed	Image	Page	✗	✗
MG-RAG (2025b)	Preprint	Qwen2.5-VL-3B-Instruct	ViT-BigG	✗	✓	Closed	Image+Text	Element	✗	✗
VRAG-RL (2025c)	Preprint	Qwen2.5-VL-7B-Instruct	ViT-BigG	✓	✗	Open	Image	Element	✗	✗
CoRe-MMRAG (2025)	ACL	Qwen2-VL-7B	ViT-BigG	✓	✓	Open	Image+Text	Page	✗	✗
Light-ColPali (2025)	ACL	PaliGemma	SigLIP-SO400M	✓	✗	Open	Image	Page	✗	✗
MM-R5 (2025a)	Preprint	Qwen2.5-VL-7B	ViT-BigG	✓	✗	Open	Image	Page	✗	✗
SimpleDoc (2025)	Preprint	Qwen2.5-VL-3B-Instruct	ViT-BigG	✗	✗	Open	Image+Text	Page	✗	✗
VisChunk (2025)	Preprint	Gemini-2.5-Pro	–	✗	✓	Closed	Image+Text	Page	✗	✗
DocVQA-RAP (2025a)	ICIC	Qwen2-VL-2B	ViT-BigG	✗	✗	Open	Image	Element	✗	✗
RL-QR (2025)	Preprint	Qwen2.5-VL-3B-Instruct	ViT-BigG	✓	✗	Open	Image	Page	✗	✗
MMRAG-DocQA (2025)	Preprint	Qwen-VL-Plus	ViT-BigG	✗	✓	Closed	Image+Text	Element	✗	✗
Patho-AgenticRAG (2025c)	Preprint	Qwen2-VL-2B	ViT-BigG	✓	✗	Open	Image	Page	✗	✓
M2IO-R1 (2025a)	Preprint	BGE-M3	–	✓	✓	Open	Image+Text	Page	✗	✗
mKG-RAG (2025)	Preprint	LLaMA-3.1-8B	CLIP ViT-L/14	✓	✓	Open	Image+Text	Element	✓	✗
DB3Team-RAG (2025)	Preprint	Llama 3.2-VL	CLIP ViT-L/14	✓	✓	Open	Image+Text	Page	✓	✗
PREMIR (2025)	EMNLP	Qwen2.5-VL-72B	ViT-BigG	✗	✓	Open	Image+Text	Element	✗	✗
ReDocRAG (2025)	ICDAR WML	Qwen2.5-VL-7B-Instruct	ViT-BigG	✓	✗	Closed	Image	Page	✗	✗
CMRAG (2025c)	Preprint	Qwen2.5-VL-7B-Instruct	ViT-BigG	✗	✓	Open	Image+Text	Page	✗	✗
MoLoRAG (2025b)	EMNLP	Qwen2.5-VL-7B	ViT-BigG	✓	✗	Open	Image	Page	✓	✗
SERVAL (2025b)	Preprint	InternVL3-14B	InternViT-300M	✗	✗	Open	Image	Page	✗	✗
MetaEmbed (2025b)	Preprint	Qwen2.5-VL-32B	ViT-BigG	✓	✗	Open	Image	Page	✗	✗
DocPruner (2025)	Preprint	Qwen2.5-VL-3B-Instruct	ViT-BigG	✓	✗	Open	Image	Page	✗	✗
RECON (Wang and Chen, 2025)	Preprint	GPT-4o-mini	–	✗	✗	Open	Image+Text	Element	✓	✗
LAD-RAG (Sourati et al., 2025)	Preprint	GPT-4o-200b-128	–	✗	✗	Open	Image+Text	Element	✓	✗
HEAVEN (Kim et al., 2025)	Preprint	Qwen2.5-VL-3B-Instruct	ViT-BigG	✗	✗	Open	Image	Page	✗	✗
DREAM (Zhang et al., 2025a)	ACM MM	InternVL2-40B	InternViT-6B	✓	✗	Closed	Image	Page	✗	✗
MARA (Wu et al., 2025a)	ACM MM	MiniCPM-V2.0	SigLIP-SO400M	✓	✗	Open	Image	Element	✗	✗
HEAR (Chen et al., 2025a)	ACM MMW	Qwen2.5-VL-32B-Instruct	ViT-BigG	✗	✓	Closed	Image+Text	Page	✗	✓
HPC-ColPali (Bach, 2025)	Preprint	PaliGemma-3B	SigLIP-SO400M	✓	✗	Open	Image	Page	✗	✗
RegionRAG (Li et al., 2025b)	Preprint	Qwen2.5-VL-3B	ViT-BigG	✓	✗	Open	Image	Element	✗	✗
IndustryRAG (Lim et al., 2025)	EMNLP Industry	Qwen2.5-VL-32B-Instruct	ViT-BigG	✗	✓	Open	Image	Page	✗	✗
COLMATE (Masry et al., 2025)	EMNLP Industry	PaliGemma-3B	SigLIP-SO400M	✓	✗	Open	Image	Page	✗	✗
LILaC (Yun et al., 2025)	EMNLP	MM-Embed	–	✗	✗	Open	Image	Element	✓	✗
HKRAG (Tong et al., 2025)	Preprint	Phi3V	CLIP-ViT-L/14	✓	✗	Open	Image	Element	✗	✗
SLEUTH (Liu et al., 2025a)	Preprint	PaliGemma-3B	SigLIP-SO400M	✗	✗	Open	Image	Page	✗	✓
Snappy (Georgiou, 2025)	Preprint	PaliGemma-3B	SigLIP-SO400M	✗	✓	Open	Image	Element	✗	✗

Table 2: **Comparison of recent Multimodal RAG methods for document understanding.** The table summarizes methods along the following dimensions: venue, backbone LLM/VLM, vision encoder, training status, OCR integration, domain scope, retrieval modality, retrieval granularity, graph incorporation, and agent usage.

RAG approaches for document understanding. Table 2 presents a systematic comparison of representative methods along several key dimensions, including domain openness, retrieval modality, retrieval granularity, graph-based integration, and agent-based enhancement. To provide a structured discussion, we elaborate on each dimension in turn: the distinction between open- and closed-domain settings (Section 3.1), the impact of retrieval modality (Section 3.2), the role of retrieval granularity (Section 3.3), agent and graph based hybrid enhancements (Section 3.4).

3.1 Open and Closed Domain

RAG addresses the limitations of LLMs in knowledge acquisition, such as knowledge cut-off, and extends their applicability to specialized domains (Lewis et al., 2020; Joren et al.; Ye et al., 2024; Gupta et al., 2024; Huang and Huang, 2024; Cheng et al., 2025). For document understanding, open-domain multimodal RAG retrieves information from large corpora of domain-specific documents to construct extensive knowledge bases. In contrast, closed-domain multimodal RAG focuses on a single document and selects only the most relevant pages for retrieval, thereby reducing input length and mitigating issues related to limited context windows and hallucination. The distinction between open-domain and closed-domain multimodal RAG is illustrated in Figure 2.

Open-Domain Multimodal RAG. Open-domain multimodal RAG enhances an LLM's knowledge in specialized domains by constructing retrieval databases from large collections of documents. Early approaches typically apply OCR to all documents to build text-based retrieval indices (Wang et al., 2022; Li et al., 2023; Chen et al., 2024c; Khattab and Zaharia, 2020), but this process is computationally expensive and inefficient. To improve scalability, recent methods such as DSE (Ma et al., 2024b) and ColPali (Faysse et al., 2024) leverage vision-language models

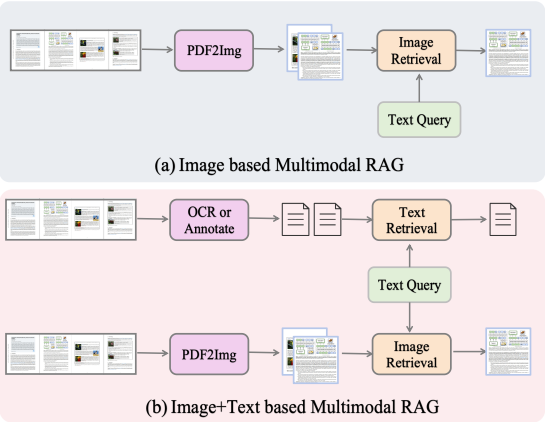


Figure 3: **Comparison of retrieval modality:** (a) image-based RAG retrieves information solely from page images, offering efficiency but limited textual detail; (b) image+text-based RAG integrates OCR/annotations with visual features, enabling richer retrieval at the cost of higher processing complexity.

(VLMs) to encode document pages directly into image embeddings, achieving significant efficiency gains. Despite these advances, most approaches still focus on reasoning within single documents and lack explicit mechanisms for integrating knowledge across sources. Addressing this limitation, M3DocRAG (Cho et al., 2024a) introduces approximate indexing to accelerate large-scale retrieval and establishes the benchmark M3DocVQA with over 3,000 documents, while VDocRAG (Tanaka et al., 2025) constructs the OpenDocVQA dataset and mitigates page-level information loss by compressing visual content into dense token representations aligned with text.

Closed-Domain Multimodal RAG. Closed-domain multimodal RAG is designed for practical scenarios where MLLMs encounter difficulties with extremely long documents or videos. Current MLLMs remain constrained by limited context windows, and long-context processing often amplifies the risk of hallucination. To address this, closed-domain approaches retrieve only the most relevant segments (*e.g.*, pages or frames) from a target document and provide them as input to the MLLM, thereby improving both efficiency and reliability. For single-document visual question answering (DocVQA), SV-RAG (Chen et al., 2024b) employs the MLLM itself as a multimodal retriever, with specialized adapters for page retrieval and evidence-based reasoning. FRAG (Huang et al., 2025a), by contrast, independently scores each frame or page, applies a Top-K selection to retain the most informative content, and then delegates answer generation to existing LMMs. CREAM (Zhang et al., 2024a) introduces a coarse-to-fine multimodal retrieval and attention-pooling integration framework, enabling effective cross-page reasoning and multi-page document comprehension for visual question answering. All approaches demonstrate that closed-domain multimodal RAG enables effective comprehension of long documents and videos without extending the model's context length.

3.2 Retrieval Modality

Early text-only RAG methods rely exclusively on textual signals for retrieval, which limits their practical utility: they require time-consuming OCR and underperform on visually rich documents. To address these limitations, current research advances multimodal RAG. One approach treats each page as an image and encodes it with the vision encoder of a VLM. Another adopts hybrid designs that pair page-level images with OCR-extracted text or auxiliary textual annotations generated by MLLMs. The resulting cross-modal representations then support retrieval independently or via score fusion, where similarity scores from different modalities combine to improve performance.

Image-based Retrieval Modality. To handle visually rich documents, most existing methods represent each page as an image and encode it with VLMs, using the VLMs' hidden states as page-level representations (see Figure 3 (a)). In parallel, the query is encoded, and page–query relevance is computed via similarity-based ranking (Ma et al., 2024b; Faysse et al., 2024; Yu et al., 2024; Chen et al., 2024b; Ma et al., 2025; Yu et al., 2025a). Building on image-based embeddings, MM-R5 (Xu et al., 2025a) introduces a reasoning-enhanced reranker that combines supervised fine-tuning and reinforcement learning to strengthen instruction following, elicit explicit reasoning chains, and leverage task-specific rewards for greater precision and interpretability. Complementing this direction, Light-ColPali (Ma et al., 2025) and HPC-ColPali (Bach, 2025) improve the efficiency of ColPali-style multi-vector retrieval by compressing patch-level representations, reducing memory and computation while largely preserving retrieval accuracy.

Image+Text based Retrieval Modality. Leveraging both image and text for retrieval mitigates the loss of fine-grained textual cues that arise when relying solely on page-level VLM encoders. The text channel is derived from OCR (Zhang et al., 2024a;

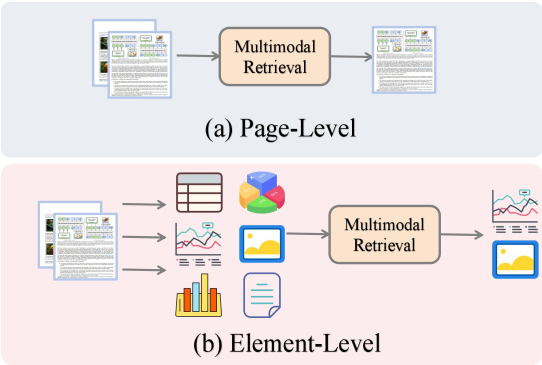


Figure 4: **Comparison of retrieval granularity in multimodal document search.** (a) Page-level: entire pages are encoded and ranked as whole units. (b) Element-level: pages are decomposed into tables, charts, images, and text blocks; retrieval operates over these elements to localize evidence and aggregate results.

Suri et al., 2025; Liu et al., 2025b; Wang et al., 2025b) or from summary annotations generated by large VLMs (Jain et al., 2025; Choi et al., 2025) (see Figure 2 (b)). VisDoMRAG (Suri et al., 2025) and HM-RAG (Liu et al., 2025b) adopt a dual-path pipeline: they retrieve and reason within each modality, then summarize and fuse the results into a single answer. By contrast, ViDoRAG (Wang et al., 2025b) and PREMIR (Choi et al., 2025) also retrieve per modality but merge candidates via a simple union before answer generation. Complementing these designs, SimpleDoc (Jain et al., 2025) uses a two-stage scheme for DocVQA: embedding-based candidate selection followed by re-ranking with VLM-generated page summaries, so that the summaries provide richer semantics for more precise evidence aggregation.

3.3 Retrieval Granularity

In document-oriented multimodal RAG, early studies typically treat the page as the atomic retrieval unit, without modeling finer structures such as tables, charts, or layout cues (see Figure 4). Recent work increasingly focuses on retrieval at a finer, within-page granularity. Some approaches explicitly encode these components to enhance retrieval accuracy, whereas others adopt a two-stage pipeline: first retrieve the most relevant pages, then perform retrieval within those pages to establish fine-grained grounding. This shift toward finer retrieval granularity enables models to deliver more precise and contextually grounded answers.

Recent multimodal RAG research demonstrates a clear evolution toward fine-grained, structure-aware evidence selection. VRAG-RL (Wang et al., 2025c) leverages reinforcement learning for region guidance, while MG-RAG (Xu et al., 2025b) and MMRAG-DocQA (Gong et al., 2025) enable multi-granularity retrieval via hierarchical indexing across pages and layouts. At the segment level, DocVQA-RAP (Yu et al., 2025a) ranks segments to suppress redundancy. Beyond segmentation, mKG-RAG (Yuan et al., 2025) aligns cross-modal entities via knowledge graphs, whereas PREMIR (Choi et al., 2025) matches queries against QA pairs for charts. Recent region-level methods like MARA (Wu et al., 2025a) and Region-RAG (Li et al., 2025b) introduce query-aligned representations and patch aggregation to reduce noise. Furthermore, HKRAG (Tong et al., 2025) captures fine-print knowledge via hybrid masking, and Snappy (Georgiou, 2025) achieves efficient localization by propagating patch-level similarity. Collectively, these approaches illustrate the shift toward increasingly fine-grained retrieval in document-heavy systems.

3.4 Hybrid Enhancements for Multimodal RAG

The main text focuses on integrating multimodal RAG with graph-based and agent-based methods. The Appendix G and H extends this discussion to more advanced integrations, highlighting open challenges and future research directions.

Graph-based Multimodal RAG. Graph-based multimodal RAG extends the framework by representing multimodal content as an explicit graph, as shown in Figure 5 (a). Nodes denote modalities or atomic content units such as pages, text spans, images, tables, and layout blocks, while edges encode semantic, spatial, and contextual relations. Retrieval and reasoning over this multimodal graph integrate heterogeneous evidence more effectively, enable finer-grained grounding, and improve the robustness and interpretability of multimodal RAG systems.

HM-RAG (Liu et al., 2025b) introduces a hierarchical multi-agent framework utilizing graph databases to capture structured relations, while mKG-RAG (Yuan et al., 2025) explicitly constructs multimodal knowledge graphs to align entities across vision and text. Building on such structured repositories, DB3Team-RAG (Xia et al., 2025) incorporates image-indexed graphs to handle complex ego-centric queries within domain-

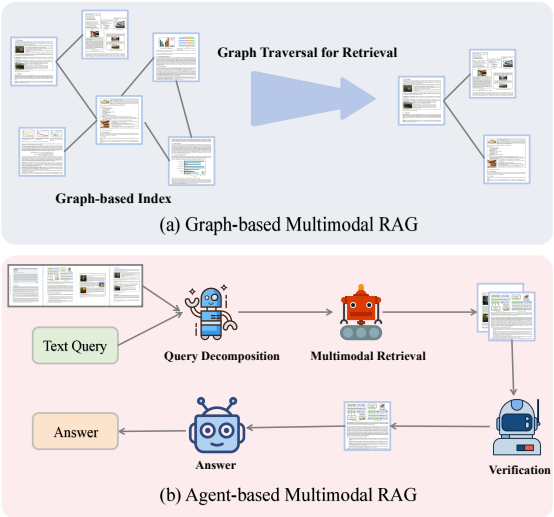


Figure 5: **Hybrid enhancements for multimodal RAG.** (a) Graph-based: documents/elements form a graph index, and retrieval proceeds via graph traversal to surface relevant neighborhoods. (b) Agent-based: an LLM agent decomposes the text query, orchestrates multimodal retrieval, verifies the gathered evidence, and synthesizes the final answer.

Dataset	# Queries	# Documents/Images	Content
TabFQuAD (2020)	210	210 (I)	
PlotQA (2020)	28.9M	224K (I)	
DocVQA (2021)	50K	12,767 (I)	
VisualMRC (2021)	30,562	10,197 (I)	
TAT-DQA (2022)	16,558	2,758 (D)	
InfoVQA (2022)	30K	5.4K (I)	
ChartQA (2022)	23.1K	17.1K (I)	
ScienceQA (2022)	21K	7,803 (I)	
DUDE (2023)	41,491	4,974 (D)	
SlideVQA (2023)	52K	14.5K (I)	
ArXivQA (2024a)	100K	16.6K (D)	
MMLongBench-Doc (2024c)	1,062	130 (D)	
PaperTab (2024)	393	307 (D)	
FetaTab (2024)	1,023	878 (D)	
SPIQA (2024)	27K	25.5K (D)	
LongDocUrl (2024a)	2,325	396 (D)	
ViDoRe (2024)	3.8K	8.3K (D)	
VisR-Bench (2024b)	471	226 (D)	
M3DoCVQA (2024a)	2,441	3,368 (D)	
VisDoMBench (2025)	2,271	1,277 (D)	
ViDoSeek (2025b)	1,142	300 (D)	
OpenDocVQA (2025)	206K	43K (I)	
UniDoc-Bench (2025)	1.6K	70K(I)	
BBox-DocVQA (2025b)	32K	4.4K(D)	

Table 3: Overview of datasets and benchmarks in multimodal RAG for document understanding. We report the number of queries, dataset size, and covered content types (Text, Tables, Charts, Slides). (D) and (I) indicate that the count refers to documents or images, respectively. **The upper part** covers widely used multimodal document understanding datasets; **the lower part** compiles recent multimodal RAG benchmarks introduced by methods surveyed in this paper to address prior limitations.

specific pipelines. Shifting focus to document topology, MoLoRAG (Wu et al., 2025b) leverages page graphs to encode logical connections for multi-page understanding. This structure-aware modeling is further refined by RECON (Wang and Chen, 2025), which builds a global graph linking intra-page visual relations with inter-page entity connections. Furthermore, LAD-RAG (Sourati et al., 2025) and LILaC (Yun et al., 2025) focus on layout-aware component graphs, employing dynamic traversal or late interaction to support multi-hop reasoning. Collectively, these methods highlight the pivotal role of graph structures as either external repositories or internal document representations in advancing reliable multimodal retrieval.

Agent-based Multimodal RAG. Agent-based multimodal RAG extends this paradigm by employing autonomous agents to orchestrate retrieval–generation interactions across modalities. These agents dynamically formulate queries, select retrieval strategies, and adaptively fuse information from text, images, tables, and other modalities (see Figure 5 (b)). Multi-agent collaboration further enables iterative reasoning, verification, and evidence refinement, improving the accuracy, reliability, and transparency of multimodal RAG systems.

ViDoRAG (Wang et al., 2025b) introduces an iterative agent workflow in which agents perform exploration, summarization, and reflection, improving multimodal retrieval and reasoning over visually rich documents. HM-RAG (Liu et al., 2025b) further extends this idea with a hierarchical multi-agent architecture, combining query decomposition, modality-specific parallel retrieval, and a decision agent that aggregates evidence through consistency voting and refinement. Adapting agentic RAG to the medical domain, Patho-AgenticRAG (Zhang et al., 2025c) enables task decomposition and multi-turn search to retrieve aligned text–image evidence from pathology textbooks while reducing diagnostic hallucinations. Along similar lines, HEAR (Chen et al., 2025a) and SLEUTH (Liu et al., 2025a) focus on improving long-document understanding by coupling VLM-based parsing with closed-loop or coarse-to-fine agent reasoning, allowing cross-modal inconsistencies to be corrected and salient evidence to be distilled into compact contexts. Overall, these approaches demonstrate how diverse agent designs enhance fine-grained retrieval and reasoning in multimodal RAG systems.

4 Dataset and Benchmark

Datasets and benchmarks commonly used in multimodal RAG for document understanding typi-

cally consist of visually rich document collections. We compile the most widely adopted datasets and benchmarks for this task, reporting their query volume, dataset scale, and data types, such as text, tables, charts, and slides. The representative datasets and benchmarks are presented in the upper part of Table 3. They support the training and evaluation of multimodal models and also serve as essential resources for constructing broader evaluation frameworks. Nevertheless, these resources still exhibit important limitations, motivating the development of more diverse and realistic benchmarks.

Many studies have revealed limitations in multimodal RAG systems, leading to the development of diverse benchmarks summarized in the lower half of Table 3. ColPali (Faysse et al., 2024) proposes ViDoRe, a comprehensive benchmark covering academic and practical tasks across domains such as energy, government, and healthcare; while SV-RAG (Chen et al., 2024b) builds VISR-BENCH from a large-scale, manually validated dataset with high task diversity. To overcome single-document evaluation, M3DocVQA (Cho et al., 2024a), VisDoMRAG (Suri et al., 2025), and VDocRAG (Tanaka et al., 2025) extend evaluation to cross-document open-domain scenarios using M3DocVQA, VisDoMBench, and OpenDocVQA, respectively. Focusing on large-scale retrieval closer to real-world applications, ViDoRAG (Wang et al., 2025b) introduces ViDoSeek, a benchmark for RAG evaluation with uniquely answerable queries. Furthermore, UniDoc-Bench (Peng et al., 2025) establishes a document-centric MM-RAG benchmark, enabling systematic comparisons of multimodal retrieval and fusion strategies on real-world PDFs through unified text, table, and figure evidence linking. BBox-DocVQA (Yu et al., 2025b) provides a DocVQA dataset with bounding-box grounding for supervision of spatial reasoning and evidence localization.

We also present the performance of different multimodal RAG methods across various benchmarks, along with a detailed explanation of the evaluation metrics and their computation. The full details are provided in Appendix A.

5 Application

Multimodal RAG increasingly serves document understanding across finance, scientific research, and survey analysis. In finance, MultiFinRAG (Gondhalekar et al., 2025) improves question answering over reports by jointly modeling narrative text, tables, and figures, while FinRAGBench-V (Zhao et al., 2025) provides a benchmark that emphasizes visual citation for transparent evidence traceability in financial documents. In the scientific domain, HiPerRAG (Gokdemir et al., 2025) enables cross-modal retrieval and reasoning at the scale of millions of research papers, and CollEX (Schneider et al., 2025) supports interactive exploration of multimodal scientific corpora. In the social sciences, a Eurobarometer-based framework embeds RAG with multimodal LLMs (Papageorgiou et al., 2025) to unify text and infographics, improving the interpretability of survey data. Taken together, these applications demonstrate how multimodal RAG strengthens the capacity to understand and leverage complex documents across fields.

6 Challenge, Critical Analysis and Industry Deployment

Due to space constraints, extended discussions are deferred to the appendix. Appendix D outlines key open challenges and future directions in multimodal RAG, focusing on efficiency, training paradigms, granularity, and security. Appendix E presents a concise critical analysis of fundamental limitations and representative failure cases beyond aggregate benchmarks. Appendix F addresses industrial deployment considerations, highlighting practical constraints, efficiency trade-offs, and representative open-source systems.

7 Conclusion

This survey provides a systematic overview of multimodal RAG for document understanding. We analyze methodological advances across retrieval modalities, domain settings, retrieval granularity, and the incorporation of graph-based and agent-oriented architectures, highlighting how these developments enhance understanding over visually rich documents. We further consolidate key datasets, benchmarks, and applications in finance, scientific literature, and social analysis, illustrating the broad impact of multimodal RAG. Despite these advances, challenges remain in efficiency, fine-grained multimodal representation, and robustness in real-world deployment. Addressing these issues will be crucial for future advancement, and we hope this work provides a foundation for advancing multimodal RAG toward reliable and generalizable document AI.

Limitations

Although this survey aims to provide a comprehensive synthesis of multimodal RAG for document understanding, several limitations remain. First, while we highlight practical applications, our analysis of real-world deployment challenges such as user-centered evaluation, system integration, and deployment scalability remains preliminary. Broader socio-technical aspects of multimodal RAG systems deserve further exploration in future work. Second, although we summarize major datasets and benchmarks, a more systematic investigation into data quality, annotation consistency, inter-domain transferability, and evaluation alignment across modalities would provide deeper insights into their generalizability and real-world relevance. Furthermore, as multimodal RAG for document understanding is an emerging and rapidly evolving field, newly released datasets, models, and evaluation protocols continue to reshape the landscape. To address this dynamic nature, this survey will be periodically updated and complemented by an open repository to track ongoing progress and facilitate community collaboration.

Ethics Statement

Our work is a survey of existing literature and does not introduce new models, algorithms, or datasets. Therefore, the survey itself does not create new risks. However, we acknowledge that the technologies we review, *i.e.,* multimodal RAG for document understanding, have some potential risks: 1) bias and discrimination inherited from the training data, and 2) the generation of misinformation due to model hallucination. We highlight that addressing these ethical challenges is a critical direction for future research.

The Use of AI assistants. AI assistants (ChatGPT) are used to correct potential grammatical inaccuracies in the manuscript. AI assistants do not participate in research ideation.

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In the appendix, a more detailed introduction to datasets and benchmarks is first provided, together with comprehensive evaluations of representative methods on these benchmarks (Appendix A). Appendix B then presents evaluation metrics for multimodal RAG, explicitly distinguishing retrieval-oriented and generation-oriented assessments, followed by a systematic overview of commonly used training loss functions and interpretations of their roles in multimodal RAG systems (Appendix C). Beyond methodological foundations, open challenges and future research directions of multimodal RAG systems are extensively discussed in Appendix D, while a focused critical analysis examining fundamental limitations, unresolved tensions, and representative failure cases is presented in Appendix E. Practical considerations for industrial deployment and real-world usage are analyzed in Appendix F. In addition, the integration of multimodal RAG with agent-based and graph-based paradigms is examined in greater depth, with detailed analyses provided in Appendix G and H, respectively. Finally, Appendix I summarizes the key contributions of all reviewed methods, offering a concise reference for rapidly understanding their core ideas.

A Dataset and Benchmark

In the main body, we provide a systematic introduction to the datasets and benchmarks that are widely used for multimodal RAG in document understanding. For each dataset or benchmark, we include a more detailed description, as summarized in Table 6, which lists the data sources and key characteristics. For instance, DocVQA (Mathew et al., 2021) is derived from the UCSF Industry Collections, InfoVQA (Mathew et al., 2022) originates from diverse infographics, and TAT-DQA (Zhu et al., 2021) is constructed from financial reports containing semi-structured tables and text.

In addition, we compile the evaluation results of various multimodal RAG methods on widely used benchmarks, including DocVQA (Mathew et al., 2021), InfoVQA (Mathew et al., 2022), SlideVQA (Tanaka et al., 2023), and MMLongBench-Doc (Ma et al., 2024c), as presented in Table 4. These results provide a clear comparison of the strengths and weaknesses of different approaches. The evaluation of multimodal RAG performance typically falls into two categories: retrieval and generation, which are presented in the upper and lower parts of Table 4, respectively. Retrieval evaluation focuses on the accuracy of the retrieved pages, whereas generation evaluation measures the correctness of model outputs when the retrieved pages are combined with the user query as input. Since different methods adopt slightly different metrics, we annotate these variations in the table, while aligning comparable metrics to facilitate direct comparison. Detailed explanations of these metrics are provided in Appendix B.

B Evaluation Metrics

The evaluation of multimodal RAG methods typically involves two aspects: retrieval evaluation and generation evaluation. Retrieval primarily measures the system's ability to accurately retrieve relevant multimodal information from a large corpus. Generation, on the other hand, evaluates the quality of the model's produced outputs conditioned on the retrieved context. We list the most commonly used metrics along with some newly designed ones that address the limitations in the following.

B.1 Retrieval Evaluation

In the context of multimodal RAG, a variety of metrics are commonly employed to evaluate the performance of the retriever module. Popular measures include Accuracy, Recall, Precision, F1-Score (Christen et al., 2023), Mean Reciprocal Rank (MRR) (Adjali et al.; Nguyen et al., 2024), and Normalized Discounted Cumulative Gain (nDCG) (Järvelin and Kekäläinen, 2002).

A widely used measure is Top-K Accuracy, which reflects the hit rate of retrieval.

$$\text{Top-}K \text{ Accuracy} = \frac{1}{|Q|} \sum_{q \in Q} \mathbf{1}\Big(\mathrm{Rel}(q) \cap \mathrm{Ret}_K(q) \neq \varnothing\Big), \tag{5}$$

where, for a given query q, $\mathrm{Ret}_K(q)$ denotes the set of the top-K results returned by the retrieval system, $\mathrm{Rel}(q)$ denotes the set of all ground-truth relevant documents or modality segments, and Q denotes the collection of queries. The same symbols appearing in the following formulas carry the same meanings.

Recall@K is usually used to quantify retrieval coverage, measuring how many of the ground-truth relevant items are captured within the top K results:

$$\mathrm{Recall@}K = \frac{1}{|Q|} \sum_{q \in Q} \frac{|\mathrm{Rel}(q) \cap \mathrm{Ret}_K(q)|}{|\mathrm{Rel}(q)|}. \tag{6}$$

Method	Metric	DocVQA	SlideVQA	InfoVQA	MMLongBench-Doc
Retrieval Evaluation					
SV-RAG (Chen et al., 2024b)	Top-5	87.0	98.8	–	84.8
DSE (Ma et al., 2024b)	R@10	–	84.6	–	–
VisRAG (Yu et al., 2024)	R@10	91.20	97.39	97.08	–
CMRAG (Chen et al., 2025c)	R@10	–	–	–	64.12
RegionRAG (Li et al., 2025b)	R@10	99.4	98.4	99.5	–
VisRAG (Yu et al., 2024)	MRR@10	75.37	91.85	86.37	–
CMRAG (Chen et al., 2025c)	MRR@10	–	–	–	47.64
LILaC (Yun et al., 2025)	MRR@10	78.75	84.43	86.83	–
ColPali (Faysse et al., 2024)	nDCG@5	54.4	–	81.8	–
ColQwen2 (Faysse et al., 2024)	nDCG@5	61.5	–	89.7	–
ColQwen2.5 (Faysse et al., 2024)	nDCG@5	63.6	–	92.5	–
VDocRAG (Tanaka et al., 2025)	nDCG@5	–	77.3	72.9	–
Light-ColPali (Ma et al., 2025)	nDCG@5	53.4	91.7	82.8	73.3
Light-ColQwen2 (Ma et al., 2025)	nDCG@5	56.6	92.9	89.5	77.0
RegionRAG (Li et al., 2025b)	nDCG@5	93.1	90.3	94.8	–
HKRAG (Tong et al., 2025)	nDCG@5	–	74.3	71.9	–
DSE (Ma et al., 2024b)	nDCG@10	–	75.3	–	–
CMRAG (Chen et al., 2025c)	nDCG@10	–	–	–	52.10
Generation Evaluation					
VisRAG (Yu et al., 2024)	EM	67.17	60.97	66.43	–
FRAG (Huang et al., 2025a)	EM	–	72.7	–	–
LILaC (Yun et al., 2025)	EM	65.48	55.57	60.91	–
SV-RAG (Chen et al., 2024b)	PNLS	76.0	77.0	–	49.0
CRAEM (Zhang et al., 2024a)	ANLS	79.4	–	53.6	–
M3DocRAG (Cho et al., 2024a)	ANLS	84.4	–	–	–
VisDoMRAG (Suri et al., 2025)	ANLS	–	67.2	–	–
VDocRAG (Tanaka et al., 2025)	ANLS	–	56.4	64.6	–
FRAG (Huang et al., 2025a)	ANLS	87.4	–	–	–
ReDocRAG (López et al., 2025)	ANLS	73.7	–	63.6	–
M3DocRAG (Cho et al., 2024a)	G-Acc	–	–	–	21.0
FRAG (Huang et al., 2025a)	G-Acc	80.5	–	–	37.9
VRAG-RL (Wang et al., 2025c)	G-Acc	–	69.3	–	24.9
SimpleDoc (Jain et al., 2025)	G-Acc	–	–	–	60.58
MMRAG-DocQA (Gong et al., 2025)	G-Acc	–	–	–	52.3
CMRAG (Chen et al., 2025c)	G-Acc	–	–	–	43.25
MoLoRAG (Wu et al., 2025b)	G-Acc	–	–	–	41.01
RECON (Wang and Chen, 2025)	G-Acc	–	66.12	–	–
LAD-RAG (Sourati et al., 2025)	G-Acc	82.9	–	–	45.0
DREAM (Zhang et al., 2025a)	G-Acc	–	–	–	27.3
MARA (Wu et al., 2025a)	G-Acc	84.64	73.40	68.02	–
SLEUTH (Liu et al., 2025a)	G-Acc	–	–	–	52.77

Table 4: Evaluation results of RAG methods. The upper block shows **retrieval evaluation** and the lower block shows **generation evaluation**. Different background shades are used to separate the two parts.

Precision@K instead measures accuracy, i.e., the proportion of retrieved items among the top K that are relevant:

$$\text{Precision@}K = \frac{1}{|Q|} \sum_{q \in Q} \frac{|\text{Rel}(q) \cap \text{Ret}_K(q)|}{K}. \tag{7}$$

The F1-Score is often adopted as the harmonic mean of Precision@K and Recall@K, widely used to assess the correctness of retrieved entities or factual fragments in both the retrieval module and the generation process (Li et al., 2024c):

$$\text{F1@}K = \frac{1}{|Q|} \sum_{q \in Q} 2 \cdot \frac{\text{Pr}_K(q) \cdot \text{Re}_K(q)}{\text{Pr}_K(q) + \text{Re}_K(q)}, \tag{8}$$

where, $\text{Pr}_K(q)$ represents Precision@K, and $\text{Re}_K(q)$ represents Recall@K.

However, the metrics above are insensitive to the ranking order within the top K. In practice, placing highly relevant or informative items at earlier positions is crucial for effective RAG. Adjali et al.; Nguyen et al. (2024) utilize MRR@K to emphasize the position of the first relevant item:

$$\text{MRR@}K = \frac{1}{|Q|} \sum_{q \in Q} \frac{\mathbf{1}\big(\text{rank}_K(q) \leq K\big)}{\text{rank}_K(q)}, \tag{9}$$

where $\text{rank}_K(q)$ denotes the position of the first relevant document within the top-K retrieved results for query q; if no relevant item appears within the top K, the reciprocal rank is set to 0.

Similarly, Zhao et al. (2025); Faysse et al. (2024) employ nDCG@K to penalize relevant items that appear lower in the ranking, thereby rewarding

systems that surface high-quality evidence earlier:

$$\text{nDCG@}K = \frac{1}{|Q|} \sum_{q \in Q} \frac{\text{DCG@}K(q)}{\text{IDCG@}K(q)}, \quad (10)$$

where

$$\text{DCG@}K(q) = \sum_{i=1}^{K} \frac{2^{\text{rel}_{q,i}} - 1}{\log_2(i+1)}. \quad (11)$$

Here, $\text{rel}_{q,i}$ represents the graded relevance of the i-th retrieved item for query q. The denominator $\text{IDCG@}K(q)$, called the *ideal DCG*, represents the maximum possible DCG that could be achieved for query q if all relevant items were perfectly ranked at the top of the list.

B.2 Generation Evaluation

In the context of Multimodal RAG, the primary objective of generation quality evaluation is to assess the quality and consistency between model-generated text and reference answers. This involves not only measuring the correctness of the responses but also considering aspects such as fluency, information coverage, and logical coherence. To achieve a comprehensive evaluation, this study examines a wide range of metrics. The earliest are soft matching metrics (*e.g.*, BLEU (Papineni et al., 2002), ROUGE (Lin, 2004), METEOR (Banerjee and Lavie, 2005)), which rely on n-gram overlap for a soft lexical evaluation that allows partial and flexible matching. They mainly assess fluency and information coverage of generated text. With the rise of question answering and reading comprehension tasks, strict matching metrics (*e.g.*, Exact Match (Rajpurkar et al., 2016), ANLS (Biten et al., 2019), PNLS (Chen et al., 2024a)) are introduced, focusing on exact or near-exact correspondence with reference answers to measure form-level correctness. More recently, driven by the advances in pretrained language models, semantic matching metrics (*e.g.*, BERTScore (Devlin et al., 2019), RoBERTa (Liu et al., 2019), G-Acc (Ma et al., 2024c)) have become prominent, enabling the assessment of deeper semantic consistency through contextual embeddings. By combining these three categories of metrics, generation quality can be evaluated holistically across surface, exact matching, and semantic alignment.

Soft Matching Metrics. The earliest approaches to generation quality evaluation adopt soft matching metrics, which rely on n-gram overlap to provide a soft lexical evaluation that tolerates partial and flexible matching between generated and reference texts. Among them, BLEU (Papineni et al., 2002) is one of the most representative metrics. BLEU evaluates the similarity between generated text and reference text based on n-gram overlap with a brevity penalty (BP). The BLEU score is defined as:

$$\text{BLEU} = \text{BP} \cdot \exp\left(\sum_{n=1}^{N} w_n \log p_n\right), \quad (12)$$

where p_n is the precision for n-grams and w_n is the weight assigned to each n-gram order. The brevity penalty (BP) is given by:

$$\text{BP} = \exp\Big(\min\Big(0,\, 1 - \frac{r}{c}\Big)\Big), \quad (13)$$

where c is the candidate (generated) length and r is the reference length.

Compared to BLEU (Papineni et al., 2002), ROUGE (Lin, 2004) evaluates the overlap between generated and reference texts at the n-gram level, and is widely used in summarization tasks. The ROUGE-N score is defined as:

$$\text{ROUGE-}N = \frac{\sum_{\text{ref}} \sum_{n \in \text{ref}} \min\big(S_n, R_n\big)}{\sum_{\text{ref}} \sum_{n \in \text{ref}} R_n}, \quad (14)$$

where S_n and R_n denote the counts of a given n-gram in the system output and reference, respectively. ROUGE-L leverages the Longest Common Subsequence (LCS) between the system output and the reference to capture sentence-level structural similarity. Its recall-oriented form is given by:

$$\text{ROUGE-L} = \frac{\text{LCS}(S, R)}{|R|}, \quad (15)$$

where LCS(S, R) denotes the length of the longest common subsequence between the system output S and the reference R, and |R| is the length of the reference.

Compared to BLEU and ROUGE, METEOR (Banerjee and Lavie, 2005) emphasizes semantic matching beyond exact n-gram overlap. It incorporates stemming, synonym matching, and a penalty for word order differences to better capture the similarity between system outputs and references. The METEOR score is defined as:

$$\text{METEOR} = F_\alpha \cdot (1 - P), \quad (16)$$

where F_α is a weighted harmonic mean of precision (P_{pre}) and recall (P_{rec}), given by:

$$F_\alpha = \frac{P_{rec} \cdot P_{pre}}{\alpha \cdot P_{pre} + (1 - \alpha) \cdot P_{rec}}, \quad (17)$$

and P is a fragmentation penalty based on word order:

$$P = \gamma \left(\frac{ch}{m}\right)^{\beta}, \tag{18}$$

where ch denotes the number of chunks (i.e., contiguous matched word sequences), m is the total number of matched words, and α, β, γ are tunable parameters.

Strict Matching Metrics. In contrast to soft matching metrics, strict matching metrics emphasize exact or near-exact correspondence between generated and reference answers. They assess the consistency and form-level correctness of model outputs, directly reflecting the factual accuracy of the generated responses.

The most representative metric in this category is Exact Match (EM) (Rajpurkar et al., 2016), which computes the percentage of predictions that exactly match one of the reference answers:

$$\text{EM} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{1}(o_i \in A_i), \tag{19}$$

where o_i denotes the predicted answer, A_i is the set of groundtruth answers, and $\mathbf{1}(\cdot)$ is the indicator function.

With the advancement of generative models and their increasing generalization capabilities, more recent metrics have been introduced. Average Normalized Levenshtein Similarity(ANLS) (Biten et al., 2019) is designed to provide a soft evaluation of string-based answers. ANLS is defined as below:

$$\text{NLS}(a_{ij}, o_i) = 1 - \frac{\text{LD}(a_{ij}, o_i)}{\max(|a_{ij}|, |o_i|)}, \tag{20}$$

where o_i is a given prediction, a_{ij} is a groundtruth answer, $\text{LD}(a_{ij}, o_i)$ denotes the standard Levenshtein edit distance (Lcvenshtcin, 1966), and $|\cdot|$ is the string length. The threshold τ controls the minimum similarity required for a prediction to be considered correct.

$$s(a_{ij}, o_i) = \begin{cases} \text{NLS}(a_{ij}, o_i), & \text{if NLS}(a_{ij}, o_i) \geq \tau, \\ 0, & \text{otherwise}, \end{cases} \tag{21}$$

$$\text{ANLS} = \frac{1}{N}\sum_{i=1}^{N} \max_j s(a_{ij}, o_i). \tag{22}$$

Moreover, AccANLS (Zhang et al., 2024b) integrates accuracy with ANLS similarity, aiming at addressing the issue of penalizing redundant outputs. Partial Normalized Levenshtein Similarity (PNLS) (Chen et al., 2024a) generalizes ANLS by relaxing the alignment requirement: instead of computing edit distance over the entire strings, it identifies the best-matching substring of the prediction relative to the reference. This design avoids penalizing extra prefixes or suffixes while still accounting for mismatches, insertions, and deletions within the aligned region, making it more suitable for evaluating verbose LLM outputs. Formally, PNLS still follows the NLS formulation but replaces the standard edit distance with a *partial edit distance* $\text{LD}^*(a_{ij}, o_i)$ obtained via approximate string matching (Sellers, 1980). The final score is computed as:

$$\text{PNLS}(a_{ij}, o_i) = 1 - \frac{\text{LD}^*(a_{ij}, o_i)}{\max(|a_{ij}|, |o_i'|)}, \tag{23}$$

where o_i' denotes the optimally aligned substring of the prediction o_i.

Semantic Matching Metrics. Beyond soft and strict matching metrics, semantic matching metrics have emerged to evaluate deeper semantic consistency between generated and reference texts. Metrics such as BERTScore, which leverages contextual embeddings from pretrained language models like BERT (Devlin et al., 2019) and RoBERTa (Liu et al., 2019), move beyond simple lexical overlap by capturing semantic similarity between generated and reference texts. This enables a more reliable evaluation of whether the meaning of a response is preserved, even when different phrasings are used. However, while BERTScore provides strong advantages in measuring semantic consistency, it is less suited for scenarios involving long-form, explanatory, or unanswerable responses. To address this gap, Generated Accuracy (G-Acc) (Ma et al., 2024c) has been proposed, which extends evaluation to free-form answers that emphasize reasoning, elaboration, and contextual completeness, thereby offering a more comprehensive assessment of generation quality.

C Training Loss

In multimodal RAG, the most common training objective is a ColBERT-style (Khattab and Zaharia, 2020; Faysse et al., 2024) contrastive loss. The key idea is to represent both queries and documents with multiple contextualized token embeddings and compute their similarity through a *late interaction*

mechanism. Formally, given a query q and a document d, we represent them as $\mathbf{H}_q \in \mathbb{R}^{L_q \times D}$ and $\mathbf{H}_d \in \mathbb{R}^{L_d \times D}$, where L_q and L_d denote the number of tokens in the query and document, and D is the embedding dimension. The late interaction similarity is defined as:

$$\mathrm{Sim}(q, d) = \sum_{t=1}^{L_q} \max_{1 \le m \le L_d} \langle \mathbf{h}_{q,t}, \mathbf{h}_{d,m} \rangle , \qquad (24)$$

where $\langle \cdot, \cdot \rangle$ denotes the dot product. This operator allows each query token to attend to its most relevant document token, enabling fine-grained matching.

During training, a contrastive objective (Khosla et al., 2020; Wang and Liu, 2021) is optimized over a batch of query–document pairs $\{(x_i, y_i)\}_{i=1}^{B}$. For each query x_i, the paired document y_i is the positive example, while the remaining documents in the batch act as negatives. Let $p_i = \mathrm{Sim}(x_i, y_i)$ and $n_i = \max_{j \neq i} \mathrm{Sim}(x_i, y_j)$ denote the positive and hardest negative similarities, respectively. The loss is defined as:

$$\begin{aligned} \mathcal{L} &= -\frac{1}{B} \sum_{i=1}^{B} \log \left(\frac{\exp(p_i)}{\exp(p_i) + \exp(n_i)} \right) \\ &= \frac{1}{B} \sum_{i=1}^{B} \log \left(1 + \exp(n_i - p_i) \right) , \end{aligned} \qquad (25)$$

which encourages higher similarity for the positive pair than for any in-batch negative.

This ColBERT-style loss, combining late interaction with contrastive learning, is widely adopted in multimodal RAG systems as it provides effective supervision for aligning queries and documents across both text and vision modalities.

D Challenge and Future Direction

Although multimodal RAG has made continuous progress in the field of document understanding, there are still several key challenges. Future research mainly focuses on the following aspects: efficiency, document-specific model architectures and training paradigms, granular and scalable evaluation protocols, and security and robustness for high-risk application scenarios.

Model Architectures, Training Paradigms, and Efficiency. The current VLMs (Bai et al., 2023; Chen et al., 2024d; Beyer et al., 2024) are mainly designed for general image-text benchmarks and lack specialized architectures for the unique visual structures in documents (such as diagrams, icons, tables, and complex formulas). This often leads to the inability to fully preserve fine-grained layout information and symbolic cues, prompting researchers to explore domain-specific vision encoders to better capture the structural and semantic features crucial for document understanding. In terms of training paradigms, many retrieval systems adopt the late interaction mechanism of ColBERT-style (Khattab and Zaharia, 2020; Faysse et al., 2024; Masry et al., 2025). One core limitation of this design lies in its scalar scoring method based on MaxSim, which only focuses on the most similar token pairs and ignores the broader semantic alignment relationships between tokens. Therefore, in semantic-rich document scenarios, it is difficult to capture distributed and subtle correlation signals. Future research can alleviate this problem by exploring more comprehensive token interaction goals beyond simple maximum aggregation. Efficiency is one of the core challenges of multimodal retrieval systems, especially in scenarios where thousands or even millions of documents need to be processed. Encoding based on VLMs generates a large number of visual tokens for each document (see Table 1), significantly increasing storage and retrieval computational costs. Techniques such as token compression, visual token merging, and dynamic pruning provide feasible paths to reduce this burden (Ma et al., 2025; Kim et al., 2025; Bach, 2025). However, effectively reducing computational costs without significantly compromising retrieval performance remains an important direction for future research.

Granular Understanding and Evaluation Protocols. More granular document representation is necessary (Wang et al., 2025c; Xu et al., 2025b; Yu et al., 2025a; Gong et al., 2025; Choi et al., 2025). This is because many existing models still operate at the page-level modeling, ignoring key elements such as tables, figures, footnotes, and layout-specific semantics. However, the progress in this direction is severely limited by the current benchmarks and scoring functions (Faysse et al., 2024; Mathew et al., 2022; Ma et al., 2024c). Existing datasets usually rely on single-hop retrieval on small-scale corpora and cannot effectively test the scalability or retrieval accuracy of the system. There is an urgent need to build an open-domain benchmark containing thousands of mixed-modal

documents to evaluate the needle-in-a-haystack retrieval capability. Such a benchmark needs to focus on testing the model's ability to locate specific visual elements, rather than simply retrieving relevant pages (Yu et al., 2025b). At the same time, standard metrics such as Recall@K treat pages as atomic units, which are not precise enough in multimodal scenarios because a single page often contains multiple independent information sources. We propose to introduce hierarchical metrics and visual grounding scores (Liu et al., 2024c; Deng et al., 2021; Xiao et al., 2024), which focus on retrieving specific visual evidence (such as a particular table or chart), rather than the entire page content, thereby improving the interpretability of the evaluation and supporting more complex downstream inference tasks.

Security, Robustness, and Trust. With the widespread deployment of multimodal RAG systems in high-risk fields such as finance, healthcare, and law, security and robustness have become critical issues that cannot be ignored (Shereen et al., 2025; Cho et al., 2024b; Nazary et al., 2025; Jiang et al., 2024; Xian et al., 2024). Besides hallucination and data leakage, the multimodal scenario also introduces cross-modal attack surfaces. Attackers can manipulate retrieval results through adversarial images, layouts, or visual cues, or guide the generation model to produce incorrect legal, medical, or financial conclusions, even bypassing text-based security filtering mechanisms (Abootorabi et al., 2025; Liu et al., 2025c). At the same time, most existing systems lack mechanisms for cross-modal verification of retrieval and generation of evidence sources (provenance), making targeted knowledge poisoning difficult to detect. Therefore, reliable deployment requires the introduction of privacy-preserving retrieval, verifiable generation, and risk-aware trust calibration, and the design of evaluation protocols that go beyond accuracy metrics to systematically assess the robustness of the model in adversarial and poisoning attack scenarios (Nazary et al., 2025).

E Critical Analysis

While recent methods have achieved notable gains in Multimodal RAG benchmarks, a closer examination reveals several unresolved contradictions that are often obscured by aggregate performance improvements. In this section, we critically analyze prevailing paradigms, focusing on the tension between visual and textual representations, the robustness of evaluation protocols, and the trade-offs between system complexity and practical utility.

The "OCR-Free" vs. "OCR-Based" Paradox. A growing body of work (*e.g.*, ColPali (Faysse et al., 2024), VisRAG (Yu et al., 2024)) promotes OCR-free approaches that encode document pages directly using vision–language models, thereby avoiding error propagation introduced by OCR systems. While such methods are effective at capturing layout structure and visual elements such as tables and charts, they remain vulnerable to visual hallucination when handling dense, fine-grained text or precise numerical information, as commonly found in financial and technical documents (Maleki et al., 2024; Liu et al., 2024b; Wang et al., 2024). In contrast, OCR-based pipelines sacrifice certain layout semantics but typically offer higher fidelity for text-centric retrieval tasks, particularly those requiring exact string matching or keyword search. Despite this, recent literature often frames OCR-free methods as a universal progression, overlooking their persistent weaknesses in text-intensive scenarios. This unresolved dichotomy highlights the absence of a unified representation that can simultaneously preserve visual structure and ensure symbolic precision, underscoring a fundamental limitation in current Multimodal RAG systems.

Validity and Saturation of Current Benchmarks. The rapid saturation of performance on standard benchmarks (such as DocVQA (Mathew et al., 2021) and InfoVQA (Mathew et al., 2022)) raises concerns about their validity as proxies for real-world document understanding. First, data contamination is a significant, often unaddressed risk. Given that many LLMs are pre-trained on vast web corpora, there is a non-negligible possibility that public benchmark data has leaked into the training sets, rendering high scores indicative of memorization rather than reasoning (Xu et al., 2024b; Hu et al., 2025; Zhou et al., 2025; Xu et al., 2024a; Deng et al., 2024b). Second, there is a misalignment between benchmark tasks and practical RAG scenarios. Most existing datasets focus on single-page or short-document VQA. However, the core challenge of Multimodal RAG lies in retrieving the correct needle from a haystack of thousands of pages (Faysse et al., 2024; Tanaka et al., 2025). High performance on current generation-focused benchmarks does not necessarily translate to robustness in large-scale, open-domain retrieval settings.

The Complexity–Performance Trade-off. Recent work increasingly adopts complex mechanisms such as graph-based indexing (Liu et al., 2025b; Yuan et al., 2025; Wang and Chen, 2025; Sourati et al., 2025), agentic workflows (Liu et al., 2025a; Chen et al., 2025a; Zhang et al., 2025c), and multi-round self-reflection. However, these designs often lead to only marginal performance gains (e.g., a 1–2% increase in accuracy) while significantly increasing computational overhead and inference latency. Despite this imbalance, few studies provide a clear cost–benefit analysis. For example, agent-based methods that require multiple LLM calls per query may be novel from a research perspective, but they are often impractical for real-time industrial deployment compared to simpler, well-tuned dense retrieval baselines. Overall, the literature tends to favor architectural complexity while paying insufficient attention to the resulting costs in latency and token usage.

F Industry Deployment

The main body of this survey focuses on model architectures, retrieval paradigms, datasets, and benchmarks for multimodal RAG in document understanding. Beyond methodological advances, industrial deployment plays a critical role in determining the practical impact of these systems. In real-world settings, multimodal RAG is primarily applied to large-scale industrial documents, where efficiency, reliability, and system integration are central concerns. Accordingly, this section discusses multimodal RAG from an industry perspective, with a focus on industrial document characteristics, efficiency considerations in retrieval systems, and representative open-source tools that facilitate practical deployment.

Domain-specific multimodal RAG in industry. RAG has been widely applied to industrial knowledge bases (Riedler and Langer, 2024; Liu et al., 2024a; Bourdin et al., 2025; Brehme et al., 2025; Chen et al., 2025b). In industrial knowledge management, RAG systems support tasks such as troubleshooting, maintenance, and querying internal regulations, with an emphasis on domain-specific indexing and user-oriented workflows rather than model innovation. In manufacturing, RAG is also integrated into cognitive digital twin systems (Shi et al., 2025), where it operates over structured asset representations such as Asset Administration Shells to support tasks including system integration and model alignment. More recently, Golden-Retriever (An et al., 2024) explores agentic RAG for industrial knowledge bases by combining high-quality retrieval, re-ranking, and tool-using agents to enable multi-step reasoning and coordinated data access.

Multimodal RAG is particularly suitable for industrial document analysis scenarios. In such scenarios, long documents typically contain text, tables, and charts, and have high requirements for processing efficiency and reliability in actual deployments. Financial documents can be regarded as a typical form of industrial documents, with similar characteristics in terms of structural complexity and engineering constraints. Driven by benchmarks such as TAT-DQA (Zhu et al., 2021) and FinRAGBench-V (Zhao et al., 2025), recent research has begun to focus on conducting question answering on long, visually rich documents. Systems like MultiFinRAG (Gondhalekar et al., 2025) enhance retrieval effectiveness by jointly indexing multiple modalities. IndustryRAG (Lim et al., 2025) further emphasizes efficiency by distilling domain knowledge and structural knowledge into a compact retriever, making multimodal RAG more practical for industrial deployments.

Efficiency of visual embeddings for large-scale deployment. Industrial corpora typically consist of thousands of multi-page PDFs, scanned manuals, CAD-like drawings, and complex financial charts. Storing dense visual embeddings for each page or every visual element would quickly become unmanageable in terms of memory usage and retrieval latency. Efficiency-oriented approaches (Ma et al., 2025; Yan et al., 2025; Bach, 2025; Kim et al., 2025) (such as Light-ColPali (Ma et al., 2025)) alleviate this bottleneck by compressing page-level visual representations. Light-ColPali reduces the number of patch-level embeddings through token merging while retaining the late-interaction scoring mechanism, achieving near-optimal retrieval quality with only a small portion of the original visual tokens. From a deployment perspective, these methods significantly reduce GPU memory usage and vector-store size, making it possible to index a complete industrial document collection rather than being limited to a small, carefully selected subset. When combined with a closed-domain multimodal RAG strategy and performing only the most relevant page retrieval within the document, visual embedding compression provides a practical solu-

Project	Stars (Dec. 2025)	Key features
RAGFlow (InfiniFlow, 2023)	∼70.3k	Enterprise-grade RAG engine with agents, document processing (DeepDoc), graph-based retrieval, and rich UI for production deployments.
RAG-Anything (Data, 2025)	∼11.3k	"All-in-one" RAG framework with modular pipelines, multi-backend support, and examples for text and document QA.
LightRAG (Data, 2024)	∼26.6k	Simple and fast RAG with graph-enhanced retrieval, scalable to large corpora and offering Docker/K8s deployment recipes.
AutoRAG (AI, 2024)	∼4.5k	AutoML-style framework for RAG evaluation and optimization, automatically exploring retrievers, chunkers, and generators.
RAGLite (Superlinear, 2024)	∼1.1k	Lightweight Python toolkit that implements RAG directly over DuckDB or PostgreSQL, emphasizing simplicity and SQL-native integration.
LlamaIndex (LlamaIndex, 2025)	∼46k	General framework for building RAG and agentic systems over arbitrary data sources, with extensive connectors and ecosystem.

Table 5: Representative open-source RAG frameworks frequently used in industrial-style deployments. GitHub star counts are approximate and reported as of December 2025.

tion for expanding industrial systems under strict latency and cost constraints.

Systems and open-source tooling for rapid deployment. The continuously expanding open-source RAG framework ecosystem has significantly lowered the threshold for industrial deployment by addressing practical issues such as system integration, scalability, and maintainability. The overall situation is shown in Table 5. RAGFlow (InfiniFlow, 2023) is designed for production-ready deployment and provides an end-to-end RAG engine with integrated UI, DeepDoc document processing, graph-based retrieval, and agent support, effectively reducing engineering costs in enterprise environments. LlamaIndex (LlamaIndex, 2025) supports rapid integration with heterogeneous data sources through modular ingestion, indexing, and orchestration components and can well adapt to the highly fragmented data infrastructure in industrial scenarios. RAG-Anything (Data, 2025) and LightRAG (Data, 2024) place more emphasis on simplicity and scalability. Among them, LightRAG particularly highlights graph-enhanced retrieval and containerized deployment based on Docker and Kubernetes, facilitating the construction of scalable and reproducible industrial systems. AutoRAG (AI, 2024) addresses a key challenge in industrial deployment and provides automated evaluation and configuration search (AutoML-style optimization) for retriever, chunker, and generator, supporting systematic tuning in cases of limited engineering resources. In contrast, RAGLite (Superlinear, 2024) adopts a minimalist design, directly built on DuckDB or PostgreSQL (SQL-native integration), and can naturally integrate into the existing enterprise data stack, significantly simplifying long-term maintenance work.

Discussion and open challenges. In industrial deployment scenarios, an effective multimodal RAG not only depends on technical design choices but also on the clear definition of role division, workflow, and information model throughout the system's entire lifecycle. Research and practical experience from industrial practice and deployment-oriented studies indicate that there are still several open challenges that need to be addressed at present. Firstly, the quality of retrieval and generation (Bruckhaus, 2024) needs to align with the actual expectations of domain experts rather than relying solely on general benchmarks for evaluation. Secondly, when indexing sensitive text and visual assets, sound data governance (Müller et al., 2025), access control, and auditability are indispensable. Thirdly, practical monitoring and error analysis tools are needed to accurately attribute system failures to specific modalities or processing stages. Finally, efficiency-oriented technologies such as visual embedding compression and hierarchical retrieval must strike a balance with the demand for faithful and verifiable reasoning capabilities. Solving these challenges is crucial for advancing multimodal RAG from research prototypes to reliable, industry-grade document AI systems.

G Graph-based Multimodal RAG

Before moving on to the multimodal scenario, it is necessary to review how the graph structure is introduced into the traditional, text-centric RAG. Recent review works on graph RAG (Peng et al., 2024; Procko and Ochoa, 2024; Zhang et al., 2025b) describe a general process: converting documents or knowledge bases into graph structures, selecting subgraphs or local neighborhoods relevant to the query during the retrieval stage, and generat-

ing based on graph-structured evidence rather than flat lists of chunks. Compared to vanilla RAG, this paradigm mainly has two advantages: first, it promotes multi-hop reasoning by explicitly modeling the relationships between evidence; second, by anchoring the output of the LLM on coherent evidence paths that connect originally sparse or distant information, it reduces hallucination (Zhang et al., 2025b).

Graph-based Textual RAG. One of the important research directions in the field of document-level reasoning focuses on the construction of knowledge graph (KG), which involves decomposing documents into entity-centered graphs to achieve cross-page information association (Wang and Chen, 2025). Knowledge graph-augmented generation methods such as SubgraphRAG (Li et al., 2024b), GRetriever (He et al., 2024), and ToG-2 (Ma et al., 2024a) enhance retrieval effectiveness through subgraph selection, ranking-based retrieval, or by combining dense retrieval with graph reasoning. However, these methods usually rely on manually constructed KGs, which have high construction costs and limited coverage. To address this issue, GraphRAG (Edge et al., 2024) uses LLMs to directly construct graphs from the original text and organizes them through hierarchical community detection, enabling document-level reasoning with higher computational costs. Based on this paradigm, subsequent works further explore different design choices and efficiency trade-offs. GNN-RAG (Mavromatis and Karypis, 2024) and GFM-RAG (Luo et al., 2025) focus on graph-based retrieval and scoring, respectively, supported by graph neural networks or pretrained graph foundation models for cross-document multi-hop reasoning. To reduce indexing and construction costs, KET-RAG (Huang et al., 2025b) proposes a multi-granular indexing scheme that combines lightweight KG skeletons with less costly text-based graphs. More recent variants, such as LightRAG (Guo et al., 2024) and HippoRAG-2 (Gutiérrez et al., 2025), further enhance scalability and reasoning performance by simplifying graph structures and strengthening passage-level integration.

Despite these advancements, graph-based RAG is currently mainly limited to text-only scenarios and inherits many of the limitations of textual RAG. Therefore, it is difficult to effectively model multimodal signals such as images, tables, or layouts, which are crucial for reasoning in visually rich documents.

Graph-based Multimodal RAG. Graph-based multimodal RAG extends the principles of graph RAG to visually rich documents by explicitly representing multimodal content as a graph structure for modeling. As shown in Figure 5(a), nodes correspond to atomic content units such as pages, text fragments, images, tables, and layout blocks, while edges are used to encode semantic, spatial, and logical relationships. The retrieval process is expressed as selecting a subgraph related to the query to simultaneously capture key content areas and their interrelationships. Reasoning based on this multimodal graph enables LLM to integrate heterogeneous evidence, achieve finer-grained grounding, and provide more interpretable attributions for cross-modal structures.

The early graph-based multimodal RAG systems have to some extent instantiated the various design roles of graph RAG. HM-RAG (Liu et al., 2025b) adopts a hierarchical multi-agent architecture, treating the graph database as a retrieval modality and using it in parallel with unstructured text and web sources, and aggregating the results through consistency voting. mKG-RAG (Yuan et al., 2025) and DB3Team-RAG (Xia et al., 2025) align the entities and relations in text and images, explicitly constructing multimodal knowledge graphs, thereby supporting knowledge-intensive visual question answering and domain-specific multi-turn queries. As a complement to the aforementioned knowledge-centered methods, MoLoRAG (Wu et al., 2025b) pays more attention to the document structure and retrieves coherent page sequences by modeling the logical jump relationships between pages. Recent methods have further elevated the graph structure from an auxiliary retrieval component to a core indexing and reasoning framework. RECON (Wang and Chen, 2025) constructs a global multimodal document graph by linking text and visual relations within pages and introducing entity connections between pages; while LAD-RAG (Sourati et al., 2025) and LILaC (Yun et al., 2025) emphasize layout-aware and component-level graphs, supporting multi-granular and multi-hop multimodal reasoning through subgraph retrieval using dynamic traversal or late interaction.

Discussion and open challenges. A key takeaway is that graph structures offer an effective abstraction for organizing and reasoning over multi-

modal evidence. By explicitly encoding relations among text, images, tables, and layout components, recent methods show clear advantages over flat multimodal retrieval in supporting multi-hop reasoning, fine-grained grounding, and more interpretable evidence aggregation (Edge et al., 2024; Wang and Chen, 2025; Sourati et al., 2025; Yun et al., 2025). Nevertheless, constructing reliable multimodal graphs remains nontrivial. Cross-modal alignment and layout relation extraction are often noisy and expensive, and inaccuracies at the graph construction stage can propagate to retrieval and generation, limiting robustness (Yuan et al., 2025; Xia et al., 2025).

Scalability and evaluation pose additional challenges. Large, global multimodal graphs are costly to build and traverse, motivating lightweight indexing schemes and dynamic subgraph retrieval as practical compromises (Huang et al., 2025b; Guo et al., 2024). More generally, existing systems assign very different roles to graphs, ranging from auxiliary retrieval signals to central reasoning scaffolds (Liu et al., 2025b), suggesting that clearer design principles are needed. Promising directions include adaptive graph construction that adjusts granularity based on query complexity, and hybrid pipelines that combine coarse text retrieval with on-demand multimodal graph reasoning. Finally, progress will require standardized benchmarks and metrics that jointly evaluate graph quality, cross-modal reasoning, and attribution, in order to assess generalization beyond narrow, domain-specific settings.

H Agent-based Multimodal RAG

Recent work reframes RAG as an agent-based pipeline. Surveys on agent-based RAG describe systems in which LLM-based agents actively control query rewriting, retrieval, and answer generation through planning, tool use, reflection, and multi-agent coordination, rather than following a static single-pass workflow (Singh et al., 2025). In parallel, personalization studies show a shift from personalized RAG, which injects user priors into retrieval and generation stages, to personalized agents that maintain user models and adapt retrieval strategies over time (Li et al., 2025a). From this perspective, agents serve as controllers of the RAG process, contextualizing retrieval and selecting evidence under user- and task-specific constraints.

Agent-based Textual RAG. Concrete architectures realize this idea by decomposing the RAG pipeline into interacting agents with specialized roles. MAIN-RAG (Chang et al., 2025) coordinates predictor, judge, and final predictor agents to filter noisy documents via consensus scoring and adaptive thresholds, yielding training-free gains in accuracy and faithfulness. MA-RAG (Nguyen et al., 2025a) further separates planning, step definition, evidence extraction, and QA into distinct chain-of-thought agents, improving multi-hop and ambiguous QA without fine-tuning. MMOA-RAG (Chen et al., 2025d) adopts an optimization view by modeling each RAG component as a cooperative RL agent under a shared task-level reward, aligning local decisions with end-to-end QA performance. AU-RAG (Jang and Li, 2024) extends this paradigm by using an agent to select and query heterogeneous, frequently updated data sources through descriptive metadata rather than fixed vector indices, enabling more flexible retrieval across APIs and disparate stores. Together, these methods characterize agent-based RAG as a modular and goal-driven paradigm, where specialized agents are coordinated under explicit global objectives to improve robustness, adaptability, and end-to-end performance. For multimodal document understanding (Abootorabi et al., 2025), this paradigm naturally extends to settings in which agents allocate queries across text, images, tables, graphs, and web sources, maintain cross-modal state over long interactions, and evaluate correctness using task-aligned multimodal signals.

Agent-based Multimodal RAG. Agent-based multimodal RAG instantiates these patterns by deploying agents that coordinate retrieval and generation across modalities. Agents dynamically formulate sub-queries, select retrieval strategies, and fuse evidence from text, images, tables, and layout blocks according to task requirements (see Figure 5 (b)). Through multi-agent collaboration, systems can perform iterative reasoning, verification, and evidence refinement, which improves both accuracy and transparency. ViDoRAG (Wang et al., 2025b) follows an iterative workflow in which exploration, summarization, and reflection agents traverse visually rich corpora to progressively refine retrieval results and answers. HM-RAG (Liu et al., 2025b), in contrast, adopts a more structured organization, combining a Decomposition Agent for query rewriting, modality-specific Retrieval Agents

for parallel evidence collection, and a Decision Agent that integrates outputs through consistency voting. Patho-AgenticRAG (Zhang et al., 2025c) extends this paradigm to the medical domain by coupling task decomposition and search agents with reinforcement-learned policies, enabling robust joint text and image retrieval while reducing hallucinations in diagnostic reasoning.

Other multimodal frameworks further expand the design space of agent roles. HEAR (Chen et al., 2025a) tightly couples VLM-based document parsing with a closed-loop multi-agent reasoning process, re-invoking parsers when cross-modal inconsistencies are detected. SLEUTH (Liu et al., 2025a) adopts a coarse-to-fine agent scheme that filters and distills salient textual and visual evidence into compact contexts for long-document understanding. Overall, agent-based multimodal RAG reframes multimodal retrieval and reasoning as a coordinated process among specialized agents for query formulation, modality allocation, and evidence validation. By enabling adaptive retrieval depth and structured cross-modal reasoning, it moves beyond static retrieve-then-read pipelines and is well suited for complex multimodal documents and domain-specific tasks.

Discussion and open challenges. Despite their flexibility, agent-based multimodal RAG systems introduce substantial computational and economic overhead. Multi-agent coordination often requires repeated LLM calls for planning, decomposition, retrieval, verification, and reflection, which can significantly increase latency and inference cost compared to single-pass RAG pipelines (Singh et al., 2025; Li et al., 2025a). This issue is exacerbated in multimodal settings, where agents may invoke expensive vision-language models, document parsers, or external tools multiple times. Balancing performance gains with practical efficiency thus remains a key challenge. Promising directions include adaptive agent activation, where agents are invoked conditionally based on task complexity or uncertainty, lightweight proxy models for early-stage filtering, and shared memory or caching mechanisms to reduce redundant reasoning and retrieval (Chang et al., 2025; Liu et al., 2025a).

A second open challenge concerns coordination and optimization in increasingly complex agent ecosystems. As the number of agents and modalities grows, designing stable interaction protocols, credit assignment mechanisms, and global objectives becomes nontrivial, and poorly aligned agents may amplify noise or propagate errors across modalities (Chen et al., 2025d; Wang et al., 2025b). Future research may benefit from tighter integration of learning-based controllers, such as reinforcement learning or meta-learning, to automatically discover effective agent roles, communication patterns, and stopping criteria under resource constraints (Chen et al., 2025d; Zhang et al., 2025c). More generally, principled evaluation frameworks that jointly measure answer quality, faithfulness, interpretability, and cost will be critical for guiding the development of scalable and reliable agent-based multimodal RAG systems in real-world deployments.

I Key Contribution Summary

Table 7 and 8 presents a consolidated overview of the key contributions of existing multimodal RAG approaches for document understanding. By systematically organizing and comparing these methods, this survey highlights the breadth of design choices and research directions in the field. Such a structured summary not only helps researchers quickly grasp the state of the art, but also clarifies common trends, complementary strengths, and open challenges. In doing so, it serves as a reference point for guiding future work and motivating new directions in multimodal retrieval and reasoning for complex document understanding.

Dataset	Features
PlotQA (Methani et al., 2020)	Bridges the gap to real-world plots with a large-scale dataset built from authentic charts and crowd-sourced questions, requiring complex reasoning and out-of-vocabulary answers beyond fixed vocabularies.
TabFQuAD (d'Hoffschmidt et al., 2020)	Evaluates TableQA models in realistic industry settings using a French table question-answering dataset enhanced with GPT-4V generated queries.
DocVQA (Mathew et al., 2021)	Highlights the gap between human and model performance on structured document understanding using a large-scale dataset from UCSF Industry collections.
VisualMRC (Tanaka et al., 2021)	Builds a visual machine reading comprehension dataset from multi-domain webpage documents to advance natural language understanding and generation from document images.
ChartQA (Masry et al., 2022)	Constructs a large-scale chart QA benchmark with human-written and generated questions to evaluate models on complex logical, arithmetic, and visual reasoning over charts.
InfoVQA (Mathew et al., 2022)	Benchmarks models on reasoning over layout, text, and visuals using a diverse infographic QA dataset highlighting the human–machine gap.
TAT-DQA (Zhu et al., 2022)	Samples financial reports with semi-structured tables and text to build a document QA dataset requiring discrete numerical reasoning, highlighting the gap between models and human experts.
ScienceQA (Saikh et al., 2022)	Introduces a multimodal benchmark of diverse science questions with annotated answers, lectures, and explanations to evaluate and enhance models' reasoning through chain-of-thought.
DUDE (Van Landeghem et al., 2023)	Creates a practical benchmark from multi-industry, multi-domain visually-rich documents to evaluate document AI on real-world, multi-task, and low-resource scenarios.
SlideVQA (Tanaka et al., 2023)	Builds a multi-image document QA dataset from slide decks to enable complex single-hop, multi-hop, and numerical reasoning, highlighting the gap between models and human performance.
ArXivQA (Li et al., 2024a)	Builds a scientific QA dataset from ArXiv papers to boost LVLMs' ability in interpreting abstract figures and improving mathematical reasoning.
MMLongBench-Doc (Ma et al., 2024c)	Constructs a long-context multimodal benchmark from lengthy PDFs with cross-page questions to evaluate LVLMs on document understanding.
PaperTab (Hui et al., 2024)	Extracts academic papers in PDF format for extractive, yes/no, and free-form QA.
FetaTab (Hui et al., 2024)	Gathers world knowledge documents in PDF and HTML format for free-form QA.
SPIQA (Pramanick et al., 2024)	Creates a large-scale QA dataset from scientific papers that integrates text with complex figures and tables to evaluate and advance multimodal understanding in research articles.
LongDocUrl (Deng et al., 2024a)	Integrates long-document understanding, numerical reasoning, and cross-element locating into a large-scale benchmark to expose critical gaps in current LVLMs.
ViDoRe (Faysse et al., 2024)	Unifies academic tasks with diverse document types and practical tasks across multiple domains and languages to comprehensively evaluate multimodal document retrieval.
VisR-Bench (Chen et al., 2024b)	Selects diverse visually-rich documents with tables, charts, and diagrams, and generate verified QA pairs using GPT-4o to create a benchmark highlighting multimodal reasoning and quality assurance.
M3DoCVQA (Cho et al., 2024a)	Evaluates open-domain DocVQA with M3DoCVQA, a large multi-page PDF benchmark requiring multi-hop, multimodal reasoning across text and visual elements.
VisDoMBench (Suri et al., 2025)	Leverages multiple documents with diverse modalities such as tables, charts, and slides, requiring cross-document reasoning, modality fusion, and verifiable answers.
ViDoSeek (Wang et al., 2025b)	Unifies queries and large corpora of visually rich documents to enable complex reasoning beyond image-based QA, emphasizing multimodal retrieval, cross-document comprehension, and unique answer generation.
OpenDocVQA (Tanaka et al., 2025)	Combines diverse document types, formats, and modalities into a unified open-domain collection to train and evaluate retrieval and QA models on visually-rich documents.
UniDoc-Bench (Peng et al., 2025)	Provides a unified, large-scale benchmark for evaluating multimodal RAG on real-world documents, enabling fair comparison across text-only, image-only, and multimodal retrieval settings.
BBox-DocVQA (Yu et al., 2025b)	Introduces a bounding-box–grounded DocVQA benchmark to evaluate fine-grained spatial grounding and reasoning in visually-rich documents.

Table 6: Popular datasets and benchmarks in multimodal RAG for document understanding, along with detailed descriptions of their data sources and characteristics.

Method	Key Contribution Summary
DSE (Ma et al., 2024b)	Encodes document screenshots with VLMs for retrieval, avoiding parsing and preserving full multimodal information.
ColPali (Faysse et al., 2024)	Embeds document page images into multi-vector representations with late interaction matching for efficient end-to-end retrieval.
ColQwen2 (Faysse et al., 2024)	Extends Qwen2-VL-2B to generate ColBERT-style multi-vector representations for complex text–image tasks, similar to ColPali.
CREAM (Zhang et al., 2024a)	Combines coarse-to-fine retrieval with multi-page visual attention pooling, enabling effective integration of multimodal document information.
VisRAG (Yu et al., 2024)	Introduces a VLM-based RAG pipeline that embeds documents as images, preserving multimodal information and avoiding text-parsing loss.
SV-RAG (Chen et al., 2024b)	Introduces a framework where MLLMs act as retriever and generator with two adapters for retrieval and question answering.
M3DocRAG (Cho et al., 2024a)	Unifies retrieval and reasoning across text, charts, and figures, enabling flexible multi-hop DocVQA over single or multi-page documents.
VisDoMRAG (Suri et al., 2025)	Introduces consistency-constrained modality fusion for unified multi-step reasoning across visual and textual modalities in multimodal document QA.
GME (Zhang et al., 2025d)	Advances universal multimodal retrieval by leveraging a synthetic fused-modal training dataset and an MLLM-based dense retriever, achieving state-of-the-art performance on the new UMR Benchmark.
ViDoRAG (Wang et al., 2025b)	Leverages a multi-agent, Gaussian Mixture Model-based hybrid retrieval and iterative reasoning workflow for complex understanding of visually rich documents.
HM-RAG (Liu et al., 2025b)	Decomposes queries hierarchically, retrieves from diverse modalities, and integrates results via consistency voting for robust multimodal reasoning.
VDocRAG (Tanaka et al., 2025)	Unifies visually-rich documents into image-based representations and design self-supervised pre-training tasks that compress visual information into dense tokens aligned with textual content for retrieval-augmented generation.
FRAG (Huang et al., 2025a)	Selects relevant frames to improve multimodal model generation efficiency and performance.
MG-RAG (Xu et al., 2025b)	Integrates hierarchical encoding, modality-aware retrieval, and VLM-based candidate filtering to effectively handle visually-rich documents.
VRAG-RL (Wang et al., 2025c)	Introduces an RL framework that enables VLMs to reason effectively over documents from pages to fine-grained regions.
CoRe-MMRAG (Tian et al., 2025)	Reconciles inconsistencies between parametric and retrieved multimodal knowledge through a four-stage framework with specialized training for reliable answer generation.
Light-ColPali (Ma et al., 2025)	Reduces memory usage in Visualized Document Retrieval by applying optimized token merging, preserving over 94% effectiveness with as little as 2.8% of the original memory.
MM-R5 (Xu et al., 2025a)	Enhances multimodal document retrieval by integrating supervised fine-tuning and reinforcement learning with reasoning chains and task-specific rewards.
SimpleDoc (Jain et al., 2025)	Combines embedding-based retrieval with summary-based re-ranking, enabling efficient multi-page reasoning with a single VLM agent.
VisChunk (Tripathi et al., 2025)	Leverages multimodal cues to chunk documents while preserving structural and semantic coherence, enhancing downstream RAG performance.
DocVQA-RAP (Yu et al., 2025a)	Proposes a utility-driven retrieval method for VDQA that scores evidence by its predicted contribution to answer quality, reducing reliance on mere semantic relevance.
RL-QR (Cha et al., 2025)	Applies reinforcement learning–based query rewriting without annotations, tailoring rewriters to specific retrievers and boosting RAG performance across text and multimodal databases.
MMRAG-DocQA (Gong et al., 2025)	Leverages hierarchical indexing and multi-granularity retrieval to connect in-page and cross-page multimodal evidence, enabling accurate reasoning over long, modality-rich documents.
Patho-AgenticRAG (Zhang et al., 2025c)	Enables joint text–image retrieval from pathology textbooks with agentic reasoning and multi-turn search, reducing hallucinations and improving diagnostic accuracy.
M2IO-R1 (Xiao et al., 2025a)	Enables multimodal inputs and outputs in RAG with an RL-based framework using an Inserter module for controllable image selection and placement.
mKG-RAG (Yuan et al., 2025)	Enhances RAG-based VQA by constructing multimodal knowledge graphs and employing dual-stage, question-aware retrieval to provide structured, modality-aligned knowledge for more accurate generation.
DB3Team-RAG (Xia et al., 2025)	Integrates domain-specific multimodal retrieval pipelines with unified LLM tuning and refusal training.
PREMIR (Choi et al., 2025)	Boosts multimodal retrieval by generating cross-modal pre-questions, enabling robust token-level matching across domains and languages.
ReDocRAG (López et al., 2025)	Enhances Document VQA by retrieving and reranking key evidence, achieving higher accuracy on multi-page datasets with reduced memory demand.
CMRAG (Chen et al., 2025c)	Leverages co-modality representations of text and images for joint retrieval and generation, enabling more effective document visual question answering than text-only or vision-only RAG methods.

Table 7: Key contributions of multimodal RAG methods for document understanding (Part1).

Method	Key Contribution Summary
MoLoRAG (Wu et al., 2025b)	Enhances multi-modal, multi-page DocQA by combining semantic and logic-aware retrieval through page-graph traversal, enabling LVLMs to capture overlooked logical connections for more accurate answers.
SERVAL (Nguyen et al., 2025b)	Leverages vision–language models to generate textual descriptions of document images and embed them with a text encoder for scalable zero-shot visual document retrieval.
MetaEmbed (Xiao et al., 2025b)	Employs learnable Meta Tokens to generate compact multi-vector embeddings, enabling scalable test-time trade-offs between retrieval quality and efficiency.
DocPruner (Yan et al., 2025)	Adaptively prunes redundant patch-level embeddings based on intra-document attention, substantially reducing storage costs for multi-vector VDR while preserving retrieval effectiveness.
RECON (Wang and Chen, 2025)	Proposes a two-stage multimodal knowledge graph construction framework for visually rich documents, featuring intra-page reflection to extract textual–visual entity relations and inter-page connection to integrate cross-page multimodal relations into a global graph.
LAD-RAG (Sourati et al., 2025)	Proposes a layout-aware dynamic RAG framework that constructs a symbolic document graph to model layout structure and cross-page dependencies, and enables adaptive evidence retrieval through LLM-guided interaction with neural and symbolic indices.
HEAVEN (Kim et al., 2025)	Proposes a two-stage hybrid-vector retrieval framework that combines single-vector candidate retrieval over visually summarized pages with efficient multi-vector reranking for visually rich documents.
DREAM (Zhang et al., 2025a)	Proposes a retrieval-enhanced multimodal framework that combines confidence-based and embedding-based document retrieval with a decoupled cross-page attention-aware MLLM to enable effective multi-page document understanding and visual question answering.
MARA (Wu et al., 2025a)	Proposes a multimodal adaptive RAG framework that introduces query-aligned document representations for retrieval and a self-reflective evidence controller to dynamically incorporate sufficient multimodal evidence during generation.
HEAR (Chen et al., 2025a)	Introduces a holistic extraction and agentic reasoning framework that tightly couples VLM-based structured document parsing with a closed-loop, multi-agent cross-modal reasoning system, enabling active verification and conflict-driven re-engagement for complex multi-modal document understanding.
HPC-ColPali (Bach, 2025)	Proposes a hierarchical patch compression framework that improves the efficiency of multi-vector document retrieval through quantization and attention-guided pruning while maintaining retrieval accuracy.
RegionRAG (Li et al., 2025b)	Proposes a region-level multimodal RAG framework that identifies and retrieves query-relevant visual regions via hybrid supervision and dynamic region grouping, reducing redundant visual context while improving retrieval and generation accuracy.
IndustryRAG (Lim et al., 2025)	Proposes an efficient knowledge distillation framework that transfers complementary domain and visual–structural knowledge from LLMs and VLMs into a compact domain-specific retriever, enabling effective RAG for industrial documents with complex structural elements.
COLMATE (Masry et al., 2025)	Proposes a multimodal document retrieval model with OCR-aware pretraining and late-interaction scoring, better aligning representation learning with multimodal document retrieval.
LILaC (Yun et al., 2025)	Proposes a multimodal retrieval framework that models documents with a layered component graph and performs late interaction–based subgraph retrieval, enabling efficient multi-granular retrieval and effective multihop reasoning across multimodal components.
HKRAG (Tong et al., 2025)	Proposes a holistic multimodal RAG framework that jointly models salient and fine-print knowledge through hybrid masking–based retrieval and an uncertainty-guided agentic generator, enabling more complete and accurate understanding of visually rich documents.
SLEUTH (Liu et al., 2025a)	Proposes a multi-agent, coarse-to-fine framework that collaboratively filters and distills salient textual and visual evidence from retrieved pages, synthesizing an evidence-dense multimodal context for effective long-document understanding.
Snappy (Georgiou, 2025)	Proposes a hybrid multimodal retrieval framework that fuses ColPali's patch-level similarity with OCR-extracted regions via spatial relevance mapping, enabling precise region-level evidence selection for RAG without additional training.

Table 8: Key contributions of multimodal RAG methods for document understanding (Part2).