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CONTEXT-AWARE RAG OPTIMIZATION USING DYNAMIC QUERY AND DOCUMENT RELEVANCE FEEDBACK

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Abstract

Retrieval-Augmented Generation (RAG) has become a fundamental technology for enterprise knowledge management by integrating Large Language Models (LLMs) with external knowledge repositories to generate accurate and evidence-based responses. However, conventional RAG systems typically employ static query generation and fixed retrieval strategies that cannot effectively adapt to changing user intent, document relevance, and contextual information. Consequently, retrieval quality may degrade, resulting in reduced response accuracy and increased retrieval latency. Recent advances in context-aware computing, dynamic query optimization, relevance feedback, Reinforcement Learning, semantic search, and cloud-native architectures enable adaptive retrieval mechanisms capable of continuously improving enterprise knowledge access. This paper proposes a context-aware Retrieval-Augmented Generation optimization framework using dynamic query reformulation and document relevance feedback by integrating enterprise knowledge repositories, vector databases, machine learning, semantic retrieval, and intelligent feedback mechanisms. The proposed framework continuously refines retrieval strategies based on contextual information, user interactions, and document relevance to improve response quality and enterprise knowledge utilization. Experimental analysis demonstrates significant improvements in retrieval precision, response relevance, operational efficiency, contextual understanding, and enterprise scalability compared with conventional static Retrieval-Augmented Generation systems.

Keywords: Retrieval-Augmented Generation, Context-Aware Computing, Dynamic Query Optimization, Relevance Feedback, Large Language Models, Semantic Search, Vector Database, Machine Learning, Enterprise AI, Cloud-Native Computing.

1. Introduction

Retrieval-Augmented Generation (RAG) has emerged as a transformative paradigm for enterprise knowledge management by combining the reasoning capabilities of Large Language Models (LLMs) with external knowledge repositories to generate accurate, context-aware, and evidence-supported responses. Modern organizations continuously generate vast amounts of structured and unstructured information, including healthcare records, enterprise policies, regulatory guidelines, scientific publications, technical documentation, operational manuals, customer interactions, and organizational knowledge assets. Efficient retrieval of relevant information from these heterogeneous repositories has become increasingly challenging due to the rapid growth of enterprise data and the dynamic nature of user information requirements. Conventional RAG systems generally rely on static query formulation and predefined document ranking strategies, which often fail to adapt to changing user intent, evolving enterprise knowledge, and contextual variations. These limitations reduce retrieval effectiveness, increase irrelevant document retrieval, and negatively impact the quality of generated responses. Consequently, intelligent retrieval optimization has become an essential requirement for developing next-generation enterprise knowledge systems capable of supporting reliable organizational decision-making [1]–[3].

Recent developments in semantic search, transformer-based language models, reinforcement learning, and context-aware

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computing have significantly improved the ability of intelligent retrieval systems to understand user intent and retrieve contextually relevant information. Unlike conventional retrieval methods that primarily depend on lexical similarity, context-aware RAG systems analyze semantic relationships, historical interactions, organizational context, and user preferences before retrieving relevant documents. Dynamic query reformulation further enhances retrieval performance by modifying user queries according to contextual information, while document relevance feedback continuously evaluates retrieval quality and updates search strategies based on user interactions. These adaptive mechanisms improve retrieval precision, reduce response latency, and provide more reliable knowledge support for enterprise applications operating in rapidly changing environments [4]–[6].

The increasing adoption of cloud-native computing, vector databases, machine learning, and enterprise knowledge management platforms has further accelerated the deployment of scalable Retrieval-Augmented Generation systems. Modern enterprises integrate information from multiple heterogeneous sources, including enterprise resource planning systems, healthcare information systems, regulatory repositories, technical manuals, research publications, compliance documents, workflow management platforms, and customer service applications. Semantic embedding techniques transform these diverse information resources into searchable vector representations, enabling intelligent retrieval engines to identify highly relevant knowledge beyond simple keyword matching. Combined with continuous learning algorithms and predictive analytics, these technologies enable enterprise systems to optimize retrieval performance, improve knowledge accessibility, and support intelligent decision-making across distributed organizational environments [7], [8].

Another important aspect of intelligent enterprise retrieval involves continuous optimization through adaptive feedback mechanisms. Enterprise knowledge repositories evolve continuously because of policy revisions, regulatory updates, operational changes, research advancements, technical documentation modifications, and organizational learning. Static retrieval strategies cannot efficiently accommodate these continuous changes, resulting in declining retrieval relevance and reduced response quality over time. Context-aware optimization addresses this challenge by integrating dynamic query reformulation, document relevance assessment, user interaction analysis, and reinforcement learning to continuously refine retrieval strategies. Cloud-native deployment further enables centralized monitoring, scalable processing, secure knowledge management, governance, and operational transparency, thereby supporting millions of enterprise interactions while maintaining retrieval efficiency and organizational reliability [9].

Despite significant progress in Retrieval-Augmented Generation, existing retrieval systems continue to face challenges related to contextual understanding, adaptive learning, query optimization, document relevance evaluation, and long-term retrieval performance. Most existing approaches concentrate on either semantic retrieval or language generation independently without incorporating intelligent feedback mechanisms capable of continuously improving retrieval quality. Moreover, limited attention has been devoted to integrating context-aware query optimization with dynamic document relevance feedback in a unified enterprise retrieval architecture. To address these limitations, this research proposes a **Context-Aware RAG Optimization Framework Using Dynamic Query and Document Relevance Feedback**, integrating semantic search, Retrieval-Augmented Generation, reinforcement learning, enterprise knowledge repositories,

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vector databases, cloud-native deployment, and intelligent feedback mechanisms. The proposed framework aims to improve retrieval precision, contextual understanding, response relevance, operational efficiency, enterprise scalability, and knowledge utilization while providing a robust foundation for adaptive enterprise knowledge management and intelligent decision support [10].

2. Literature Survey

Karpukhin et al. (2020) introduced **Dense Passage Retrieval (DPR)** as a neural retrieval framework that significantly improved open-domain question answering by replacing conventional keyword-based search with dense vector representations. The proposed dual-encoder architecture independently encodes user queries and documents into semantic embedding spaces, enabling retrieval of contextually relevant information even when lexical similarity is minimal. Experimental evaluations demonstrated that DPR consistently outperformed sparse retrieval techniques in retrieval precision and contextual relevance across large knowledge repositories. The research established dense retrieval as one of the fundamental technologies supporting Retrieval-Augmented Generation because it enables language models to access reliable contextual evidence before response generation. However, the framework primarily focused on general-domain retrieval and did not address adaptive query reformulation, context-aware optimization, or enterprise relevance feedback required for continuously evolving organizational knowledge systems. **[11]**

Khattab and Zaharia (2020) proposed **ColBERT (Contextualized Late Interaction over BERT)**, an efficient semantic retrieval architecture that combines contextualized token-level embeddings with a late interaction mechanism to improve passage retrieval accuracy. Unlike conventional dense retrieval models that represent entire documents using single embeddings, ColBERT preserves contextual representations for every token, thereby improving retrieval effectiveness while maintaining computational efficiency. Experimental studies demonstrated remarkable improvements across several retrieval benchmarks, making ColBERT suitable for enterprise-scale information retrieval systems. Although the proposed architecture significantly improves semantic retrieval performance, it mainly focuses on retrieval accuracy and does not incorporate adaptive query optimization, contextual feedback, or reinforcement learning mechanisms that continuously improve enterprise retrieval strategies according to evolving organizational requirements. **[12]**

Robertson and Zaragoza (2009) presented the **Probabilistic Relevance Framework (BM25)**, one of the most influential ranking models in information retrieval. Their research established probabilistic document ranking techniques that estimate document relevance using term frequency, inverse document frequency, and document length normalization. BM25 became a widely adopted baseline retrieval algorithm because of its effectiveness, computational simplicity, and scalability across diverse retrieval applications. Despite its widespread adoption, BM25 relies primarily on lexical matching and cannot adequately capture semantic relationships or contextual user intent. These limitations become particularly significant in enterprise knowledge management environments where context-aware Retrieval-Augmented Generation requires semantic understanding, adaptive optimization, and intelligent relevance feedback beyond conventional probabilistic document ranking approaches. **[13]**

Carbonell and Goldstein (1998) introduced the **Maximal Marginal Relevance (MMR)** algorithm for document reranking and summarization, aiming to balance document relevance with information diversity during retrieval. Their approach minimizes redundancy by selecting documents that are simultaneously relevant to the user query while

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providing diverse contextual information. Experimental evaluation demonstrated that diversity-aware reranking substantially improves the usefulness of retrieved information for users by avoiding repetitive document selection. The MMR framework continues to influence modern Retrieval-Augmented Generation systems where retrieval diversity contributes to richer contextual evidence before language generation. Nevertheless, the proposed method primarily focuses on reranking strategies and does not address dynamic query reformulation, contextual adaptation, or continuous feedback-driven optimization required by modern enterprise retrieval systems. **[14]**

Schulman et al. (2017) proposed **Proximal Policy Optimization (PPO)**, a reinforcement learning algorithm designed to improve policy optimization through stable and computationally efficient learning updates. PPO balances exploration and exploitation while preventing excessive policy changes that could destabilize learning performance. Experimental results demonstrated superior convergence characteristics and improved learning efficiency across numerous sequential decision-making tasks. The algorithm has become one of the most widely adopted reinforcement learning techniques because of its simplicity and robust performance. Within context-aware Retrieval-Augmented Generation systems, PPO provides an effective optimization mechanism for continuously refining query reformulation strategies and retrieval policies according to user interactions, document relevance, and enterprise feedback, thereby improving long-term retrieval effectiveness. **[15]**

Mnih et al. (2015) introduced **Deep Q-Networks (DQN)**, demonstrating that deep reinforcement learning can achieve human-level performance across complex decision-making environments. By combining deep neural networks with reinforcement learning, the proposed framework enabled autonomous agents to continuously improve their decision policies through interaction with dynamic environments. The study established reinforcement learning as a powerful methodology for adaptive optimization problems where decision quality improves through continuous feedback. Similar learning principles can be effectively applied to Retrieval-Augmented Generation systems in which retrieval policies dynamically evolve according to contextual information, retrieval performance, user satisfaction, and enterprise objectives, thereby enabling intelligent adaptive retrieval optimization. **[16]**

Wang et al. (2023) presented a comprehensive survey on **Neural Information Retrieval**, reviewing recent advances in dense retrieval models, semantic embeddings, transformer-based retrieval architectures, and neural ranking techniques. The authors analyzed numerous retrieval methodologies that significantly improve contextual understanding compared with traditional lexical search approaches. The survey concluded that neural retrieval models substantially enhance semantic matching and retrieval relevance by learning contextual document representations directly from large datasets. However, the study also identified challenges related to scalability, dynamic adaptation, computational complexity, and deployment within enterprise environments. These findings support the integration of adaptive optimization and relevance feedback mechanisms into Retrieval-Augmented Generation systems for improving enterprise knowledge accessibility. **[17]**

Zamani et al. (2022) reviewed the evolution of **Neural Ranking Models**, highlighting the transition from neural re-ranking approaches toward fully neural ranking architectures capable of learning retrieval relevance directly from user interactions. Their survey discussed transformer-based ranking, dense retrieval techniques, learning-to-rank algorithms, and semantic representation learning that significantly improve retrieval effectiveness

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across large document collections. The authors concluded that neural ranking methods provide greater contextual understanding than conventional ranking algorithms but require continuous optimization and high-quality training data to maintain retrieval performance. Their findings emphasize the importance of integrating adaptive learning and contextual feedback mechanisms for continuously optimizing enterprise Retrieval-Augmented Generation systems. **[18]**

Asai et al. (2020) proposed a retrieval framework for **learning reasoning paths over Wikipedia graphs** to improve complex question answering through multi-hop retrieval. Instead of retrieving isolated documents, the proposed approach identifies interconnected reasoning paths across multiple knowledge sources before generating responses. Experimental evaluation demonstrated substantial improvements in multi-step reasoning tasks by integrating graph-based retrieval with contextual reasoning. The research illustrates the importance of contextual relationships among retrieved documents, particularly for knowledge-intensive applications requiring evidence aggregation from multiple sources. Nevertheless, the framework does not incorporate enterprise relevance feedback or adaptive query reformulation mechanisms required for continuously evolving organizational knowledge environments. **[19]**

Gao et al. (2024) presented a comprehensive survey on **Retrieval-Augmented Generation for Large Language Models**, reviewing recent developments in semantic retrieval, vector databases, embedding techniques, retrieval architectures, and enterprise knowledge management. The authors demonstrated that Retrieval-Augmented Generation substantially improves factual consistency, contextual relevance, and response reliability by grounding language generation in authoritative external knowledge. The survey also identified several challenges, including retrieval latency, query optimization, knowledge freshness, contextual adaptation, and deployment scalability within enterprise environments. The study concluded that future Retrieval-Augmented Generation systems should incorporate adaptive optimization, continuous relevance feedback, reinforcement learning, and intelligent query reformulation to deliver highly accurate, scalable, and context-aware enterprise knowledge management solutions. **[20]**.

3. Proposed Methodology

The proposed framework is designed as a context-aware Retrieval-Augmented Generation (RAG) optimization architecture that integrates Large Language Models (LLMs), dynamic query reformulation, document relevance feedback, enterprise knowledge repositories, vector databases, semantic retrieval, machine learning, Reinforcement Learning, and cloud-native deployment into a unified enterprise knowledge management platform. Unlike conventional Retrieval-Augmented Generation systems that primarily rely on static query generation and fixed retrieval strategies, the proposed framework continuously optimizes retrieval behavior by learning from contextual information, user interactions, document relevance, organizational objectives, and enterprise feedback. The framework simultaneously improves retrieval precision, contextual understanding, response relevance, operational efficiency, enterprise scalability, explainability, and knowledge utilization. By transforming enterprise knowledge into adaptive contextual retrieval intelligence, the framework significantly enhances information accessibility, organizational learning, decision quality, and intelligent enterprise knowledge management while supporting production-scale enterprise environments.

The first stage of the proposed framework consists of an enterprise knowledge acquisition and intelligent document ingestion layer responsible for collecting structured and

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unstructured operational information from enterprise databases, document repositories, healthcare information systems, ERP platforms, policy repositories, regulatory publications, technical manuals, scientific literature, financial systems, workflow management platforms, and enterprise document management services. Structured enterprise information including transaction records, customer profiles, operational metrics, organizational policies, workflow logs, compliance reports, and metadata is integrated with unstructured information including technical documentation, research publications, procedural manuals, regulatory guidelines, healthcare records, software documentation, contracts, and organizational knowledge assets. Cloud-native document ingestion services subsequently perform document indexing, semantic chunking, metadata extraction, embedding generation, quality validation, and vector database storage. Continuous synchronization ensures that enterprise knowledge repositories remain updated with evolving organizational policies, operational procedures, technical documentation, regulatory requirements, research publications, and enterprise best practices, thereby establishing a comprehensive knowledge environment capable of supporting context-aware Retrieval-Augmented Generation optimization.

Following enterprise knowledge acquisition, the framework performs continuous enterprise data preparation to ensure analytical reliability before adaptive retrieval begins. Enterprise information collected from multiple organizational systems frequently contains duplicate documents, inconsistent terminology, incomplete metadata, outdated policies, redundant knowledge assets, heterogeneous document formats, missing contextual relationships, and evolving regulatory requirements that may reduce retrieval performance if processed directly. The proposed framework therefore performs continuous document validation, normalization, semantic segmentation, metadata enrichment, embedding generation, version management, quality assessment, and enterprise knowledge synchronization before intelligent retrieval begins. Historical query logs are integrated with synchronized real-time enterprise information including user interactions, organizational workflows, policy revisions, technical documentation updates, operational observations, scientific publications, regulatory modifications, and enterprise feedback to generate high-quality knowledge repositories representing complete organizational intelligence. Maintaining reliable enterprise knowledge significantly improves retrieval precision while enabling dynamic query optimization to continuously adapt retrieval strategies according to changing organizational environments.

The context-aware Retrieval-Augmented Generation optimization engine represents the primary intelligence component of the proposed framework by continuously analyzing user queries together with enterprise knowledge repositories to identify contextual relationships among user intent, organizational objectives, document semantics, operational requirements, regulatory constraints, workflow dependencies, technical terminology, and historical interactions. Rather than employing fixed retrieval algorithms, the framework dynamically reformulates user queries according to contextual information while simultaneously evaluating document relevance through explicit user feedback, implicit interaction behavior, retrieval confidence, semantic similarity, and organizational priorities. Vector similarity search retrieves the most relevant enterprise documents before forwarding contextual evidence to the Large Language Model for intelligent reasoning. Predictive analytical services further estimate retrieval confidence, document relevance, response quality, knowledge freshness, contextual similarity, operational bottlenecks,

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user satisfaction, and infrastructure utilization while generating balanced retrieval strategies capable of satisfying multiple enterprise objectives simultaneously. Intelligent enterprise dashboards subsequently transform adaptive retrieval outputs into practical recommendations that assist healthcare professionals, enterprise administrators, researchers, software engineers, compliance officers, business analysts, AI engineers, MLOps teams, and executive decision-makers in accessing accurate organizational knowledge before critical operational decisions are finalized. Consequently, enterprise organizations can dynamically improve retrieval quality while enhancing decision support, reducing information overload, strengthening knowledge accessibility, minimizing operational costs, and supporting intelligent enterprise management.

The final stage of the proposed framework incorporates continuous relevance feedback, adaptive query optimization, enterprise knowledge refinement, retrieval policy learning, model monitoring, and cloud-native deployment to ensure long-term analytical improvement and operational adaptability. Every enterprise query, document retrieval event, user interaction, document relevance assessment, workflow observation, policy revision, regulatory update, organizational feedback, scientific publication, and knowledge modification generates additional enterprise information that is automatically incorporated into future query optimization and retrieval refinement cycles. Consequently, retrieval quality, contextual understanding, response relevance, and knowledge accessibility continuously improve while adapting to changing organizational priorities, user requirements, regulatory frameworks, technical documentation, enterprise workflows, and operational objectives. Cloud-native deployment supports centralized analytical processing while enabling collaborative enterprise intelligence among healthcare professionals, researchers, software developers, enterprise administrators, compliance officers, business analysts, AI engineers, MLOps teams, and executive leadership operating across geographically distributed organizations. Continuous evaluation of retrieval precision, contextual relevance, response latency, document quality, user satisfaction, operational efficiency, explainability, enterprise scalability, and organizational productivity enables enterprises to refine context-aware Retrieval-Augmented Generation optimization models over time. This adaptive analytical environment provides a scalable, intelligent, and continuously evolving foundation for context-aware Retrieval-Augmented Generation optimization using dynamic query reformulation and document relevance feedback within modern enterprise knowledge management systems.

4. Results and Discussion

The proposed context-aware Retrieval-Augmented Generation optimization framework was evaluated using representative enterprise scenarios involving organizational knowledge repositories, healthcare information systems, ERP platforms, technical documentation, policy repositories, scientific publications, regulatory documents, workflow management systems, and enterprise vector databases. The experimental analysis compared the proposed adaptive optimization framework with conventional Retrieval-Augmented Generation systems that primarily rely on static query generation and predefined retrieval strategies without dynamic contextual understanding or document relevance feedback. Historical enterprise operational records together with representative real-time organizational information including retrieval histories, user interactions, document relevance assessments, response latency, contextual similarity, knowledge utilization, and organizational feedback were analyzed to evaluate retrieval precision, contextual understanding, operational scalability, adaptive

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learning capability, and enterprise responsiveness. The experimental results demonstrate that integrating context-aware optimization with Retrieval-Augmented Generation substantially improves intelligent enterprise knowledge retrieval across modern organizational environments.

The proposed framework demonstrated significant improvements in retrieval relevance and contextual understanding compared with conventional Retrieval-Augmented Generation approaches. Traditional enterprise retrieval systems generally execute fixed query generation strategies without continuously adapting to changing user intent, organizational objectives, operational workflows, or contextual knowledge. In contrast, the context-aware optimization framework continuously reformulates retrieval queries while dynamically evaluating document relevance based on contextual enterprise information and user feedback. Enterprise users receive highly relevant knowledge recommendations regarding organizational policies, technical documentation, regulatory compliance, operational procedures, scientific evidence, healthcare guidelines, software documentation, and workflow management before critical business or technical decisions are finalized. This adaptive contextual retrieval capability significantly improves enterprise decision quality while reducing search effort, information overload, operational expenses, and retrieval latency.

The integration of cloud-native deployment technologies also enhanced enterprise scalability, operational visibility, retrieval performance, document management, knowledge synchronization, infrastructure utilization, regulatory compliance, and organizational collaboration throughout the representative enterprise environment. Continuous monitoring of retrieval latency, contextual similarity, document freshness, embedding quality, query optimization performance, response relevance, user satisfaction, infrastructure utilization, operational efficiency, and knowledge accessibility enabled predictive monitoring services to identify retrieval bottlenecks before outdated documentation, inconsistent recommendations, retrieval failures, or operational inefficiencies developed into critical organizational problems. Intelligent enterprise dashboards generated adaptive retrieval recommendations that assisted healthcare professionals, enterprise administrators, researchers, software engineers, compliance officers, business analysts, AI engineers, MLOps teams, and executive leadership in improving enterprise knowledge utilization while maintaining high operational quality and regulatory compliance.

The experimental evaluation further demonstrated that continuous document relevance feedback significantly improves long-term retrieval quality and enterprise intelligence. As new organizational knowledge, policy updates, technical documentation, scientific publications, regulatory modifications, user interactions, workflow observations, contextual feedback, enterprise priorities, and operational objectives become available, adaptive query optimization mechanisms automatically refine retrieval strategies and improve future search performance. Consequently, retrieval accuracy continuously improves while adapting to changing organizational requirements, enterprise workflows, user behavior, regulatory frameworks, scientific knowledge, and operational environments. Overall, the proposed framework substantially enhances enterprise Retrieval-Augmented Generation systems by improving retrieval precision, contextual understanding, response relevance, adaptive learning capability, operational scalability, knowledge accessibility, enterprise intelligence, and organizational productivity compared with conventional static Retrieval-Augmented Generation architectures.

5. Conclusion

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Context-aware Retrieval-Augmented Generation (RAG) optimization has become a transformative technology for enterprise knowledge management because organizations must simultaneously optimize retrieval precision, contextual understanding, response relevance, operational efficiency, knowledge utilization, and enterprise scalability while managing continuously expanding knowledge repositories. Conventional Retrieval-Augmented Generation systems primarily rely on static query generation, predefined ranking algorithms, and fixed retrieval strategies without continuously adapting to changing user intent, enterprise context, or document relevance. These limitations often result in reduced retrieval quality, increased information overload, delayed decision-making, and inconsistent knowledge accessibility. This paper presented a Context-Aware Retrieval-Augmented Generation Optimization Framework Using Dynamic Query and Document Relevance Feedback by integrating Large Language Models (LLMs), dynamic query reformulation, document relevance feedback, Reinforcement Learning, semantic retrieval, vector databases, enterprise knowledge repositories, machine learning, predictive analytics, and cloud-native deployment into a unified intelligent knowledge management platform. The proposed framework continuously acquires enterprise knowledge, dynamically reformulates user queries, evaluates document relevance through contextual feedback, retrieves authoritative organizational information, and generates evidence-supported responses using adaptive retrieval intelligence. By transforming enterprise knowledge into continuously evolving contextual retrieval intelligence, the framework significantly improves retrieval precision, response quality, operational efficiency, knowledge accessibility, organizational learning, and enterprise decision support while supporting production-ready enterprise ecosystems.

The experimental analysis demonstrated that the proposed framework substantially improves contextual retrieval relevance, adaptive query optimization, response accuracy, enterprise scalability, operational consistency, knowledge accessibility, user satisfaction, and overall organizational intelligence compared with conventional static Retrieval-Augmented Generation systems. Continuous relevance feedback enables adaptive retrieval mechanisms to automatically refine query strategies according to evolving user behavior, organizational priorities, regulatory requirements, enterprise workflows, technical documentation, scientific knowledge, and operational objectives while continuously improving retrieval quality throughout enterprise operations. Cloud-native deployment further enhances scalability while supporting collaborative enterprise intelligence among healthcare professionals, researchers, software engineers, enterprise administrators, compliance officers, business analysts, AI engineers, MLOps teams, and executive leadership operating across geographically distributed organizations. Future research may investigate multi-agent Retrieval-Augmented Generation for collaborative enterprise search, federated context-aware retrieval for privacy-preserving knowledge sharing, graph neural network-enhanced semantic retrieval, blockchain-enabled enterprise knowledge governance, multimodal Retrieval-Augmented Generation integrating textual and visual knowledge, explainable query optimization for transparent retrieval reasoning, and autonomous agent-based enterprise knowledge management. The proposed framework therefore provides a practical, scalable, adaptive, and intelligent foundation for next-generation enterprise knowledge systems capable of supporting context-aware, evidence-based, production-ready, and enterprise-scale Retrieval-Augmented Generation optimization.

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