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Original Article

Retrieval-Augmented Generation (RAG) Systems for Knowledge Management

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ABSTRACT

Artificial Intelligence (AI) and Large Language Models (LLMs) have significantly transformed knowledge management by enabling intelligent, context-aware, and automated information access. However, standalone LLMs often suffer from limitations such as outdated knowledge, hallucinated responses, lack of domain-specific expertise, and limited transparency, reducing their reliability in enterprise and research applications. Retrieval-Augmented Generation (RAG) has emerged as an effective solution by combining language models with external knowledge retrieval, allowing responses to be generated using up-to-date and relevant information. This study proposes a comprehensive Retrieval-Augmented Generation framework for intelligent knowledge management systems. The framework integrates document acquisition, preprocessing, semantic embedding generation, vector database indexing, document retrieval, prompt augmentation, LLM-based response generation, response validation, and continuous knowledge base updates. It supports diverse knowledge sources, including enterprise databases, technical documents, digital libraries, and research repositories, while incorporating sparse, dense, hybrid retrieval, and neural reranking techniques to improve retrieval accuracy. The proposed framework is evaluated using retrieval precision, recall, F1-score, response relevance, latency, grounding accuracy, and user satisfaction. Results demonstrate improved semantic understanding, reduced hallucinations, enhanced factual correctness, and real-time knowledge updates compared with conventional keyword-based knowledge management systems. The study also discusses future directions, including multimodal RAG, graph-enhanced retrieval, federated knowledge management, continual learning, and autonomous enterprise knowledge assistants, establishing RAG as a robust foundation for trustworthy and intelligent knowledge-driven AI systems.

KEYWORDS

Retrieval-Augmented Generation (RAG), Knowledge Management, Large Language Models, Artificial Intelligence, Semantic Search, Vector Database, Information Retrieval, Transformer Models, Enterprise Knowledge Systems, Natural Language Processing.

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1. INTRODUCTION

1.1. Background

The proliferation of digital information has empowered organisations to produce, manage and make use of knowledge in new and also innovative ways for service, and for strategic choices. Structured and unstructured data are produced at enormous rate by enterprises through enterprise systems, cloud platforms, IoT devices, customer interactions, research publications and digital communication channels. The traditional knowledge management systems, which are mostly based on a document repository, a metadata indexing and a technique of searching using keywords, are not the best suited to determine the meaning of the user query in its context, thus leading to incomplete or irrelevant search results. The recent developments in AI, especially transformer-powered Large Language Models (LLMs), have significantly improved the understanding and generation of natural language. These models, however, rely on knowledge learned prior to training, and do not have direct access to newly acquired organizational information, which can result in outdated or incorrect answers. Retrieval-Augmented Generation (RAG) overcomes these limitations by combining semantic document retrieval with generative language models, enabling the system to retrieve relevant organizational knowledge before generating responses. This integration enhances factual precision, contextual appropriateness, explainability, and adaptability and decreases hallucination outputs. RAG has emerged as a promising solution for knowledge management in the intelligent enterprise, offering efficient information retrieval, evidence-based decision-making, and digital transformation across various areas of the organization.

1.2. Need for Retrieval-Augmented Generation Systems for Knowledge Management

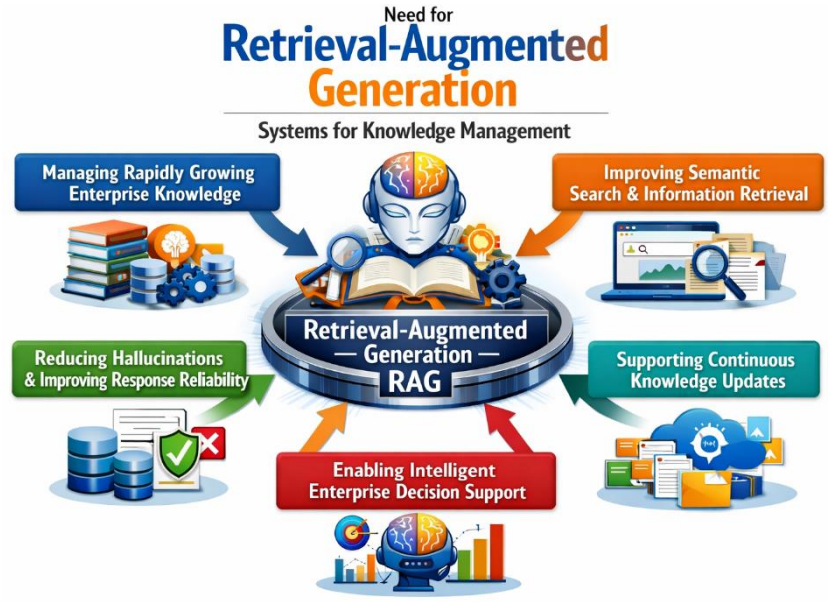

Fig 1 - Need for Retrieval-Augmented Generation Systems for Knowledge Management

1.2.1. Managing Rapidly Growing Enterprise Knowledge

In today's world, enterprise applications, cloud services, customer interactions, research, technical documentation and business transactions continuously produce large amounts of

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information. The larger the organization's knowledge, and the greater the number of documents in its archives, the harder it will be to find the relevant facts and information in the conventional knowledge management system. In cases where knowledge is spread out in a variety of different, disparate sources, conventional keyword-based search methods can often miss out on the most relevant documents. To overcome these challenges, organizations need to be able to efficiently organize, access, and utilize large-scale knowledge repositories, and this is where Retrieval-Augmented Generation (RAG) comes in.Retrieval-Augmented Generation (RAG) is a solution that combines advanced language models with semantic retrieval, allowing organizations to manage and access extensive knowledge bases efficiently. This feature allows workers to easily access the correct and relevant information, enhancing the efficiency of the operations and productivity of the organization.

1.2.2. Improving Semantic Search and Information Retrieval

Traditional Knowledge Management systems mainly rely on the keyword matching technique that fails to consider the context of user queries. As a result, users might get search results that are missing or not relevant if the word used to represent the same concept is different. Retrieval-Augmented Generation (RAG) augments the RAG API with semantic search capabilities by transforming documents and user queries into dense vector representations that retain their semantic meaning. The system returns documents by semantic similarity rather than exact keyword matching—this enables it to better understand the intent of the user. This can greatly boost search retrieval accuracy, minimize irrelevant search results, and help organizations offer smarter and more effective access to enterprise knowledge.

1.2.3. Reducing Hallucinations and Improving Response Reliability

While LLM's are very good at understanding language and generating text, they can still arrive at answers that are incorrect or even fabricated when they are asked a question that is not in their knowledge base. These hallucinatory reactions may have a harmful impact on enterprise decision-making. Retrieval-Augmented Generation (RAG): This overcomes this limitation by retrieving relevant organizational documents prior to generating responses.The language model uses validated contextual information from the knowledge repository, thus producing factually correct, evidence-based responses that are consistent with the current knowledge of the organization. This not only ensures more consistent responses but also increases user trust and reduces the risk of any inaccurate or unsupported information.

1.2.4. Supporting Continuous Knowledge Updates

The knowledge possessed by an organization is dynamic, due to policy changes, technology changes, business process changes, regulatory changes, and newly created documents. Traditional language models need to be costly and repeatedly retrained in order to learn new information, which is not appropriate for high dynamic environments. The flexibility of the solution is that newly added documents can be embedded and indexed in the vector database without having to change the language model. This allows organizations to constantly have updated and accurate knowledge

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repositories, while also ensuring that users always have access to the most current knowledge. Ongoing knowledge updates help organizations stay agile and make informed decisions.

1.2.5. Enabling Intelligent Enterprise Decision Support

Reliable, relevant and timely knowledge is essential for effective organizational decision making. Frequently workers need to be able to access the correct data from a variety of sources such as various departments, technical manuals, policy documents, research reports and historical records in order to carry out their work efficiently. Retrieval-Augmented Generation combines semantic retrieval, contextual understanding, and intelligent language generation, ensuring concise, evidence-based, and context-appropriate responses. The framework provides real-time delivery of accurate information, minimizing manual document searching, aiding knowledge discovery, enhancing collaboration and organizational learning. As such, Retrieval-Augmented Generation is a strong foundation for intelligent enterprise knowledge management systems, driving digital transformation, operational excellence, and data-driven strategic decision-making.

1.3. Retrieval-Augmented Generation (RAG) Systems for Knowledge Management

By leveraging the advanced language understanding capabilities of Large Language Models (LLMs) and semantic information retrieval, Retrieval-Augmented Generation (RAG) has become a game-changing method for intelligent knowledge management. While conventional knowledge management systems focus mainly on keyword search and document storage, RAG can dynamically search relevant data from external knowledge sources before generating the answer. This design allows the system to seamlessly integrate the reasoning and language generation power of transformer-based models with enterprise knowledge, leading to more precise, context-aware, and evidence-backed responses. The documents in an organization are gathered from multiple sources in the databases, cloud storage, technical manuals, research publications, policy documents, and knowledge bases, then preprocessed, semantic chunked, and embedded in a vector database, in a typical RAG framework. The user enters a natural language question, which is then translated into a semantic embedding and compared to the vectors of the previously indexed documents to get the most relevant knowledge fragments. The retrieved documents are then added to the prompt that the language model is fed with, which enables the model to create responses based on the verified organizational information. This method helps in minimizing hallucinated answers, factual correctness, and making the generated answers more explainable with providing real evidence. Moreover, RAG allows businesses to keep their knowledge bases up-to-date by simply adding new documents and re-indexing them, without the need for costly retraining of the language model. The ability to do this makes the framework very flexible to a changing business environment in which policies, procedures, technical documentation and regulatory requirements are continually changing. Besides, semantic retrieval techniques help information become more accessible, as they allow users to access information even if they are using different terms and have a better understanding of the meaning of the information. For these reasons, you can find several examples of its use in enterprise search, customer support systems, healthcare information systems, legal research, financial services, education, and industrial search and information systems. Overall, RAG offers a comprehensive and

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reliable solution for organizations looking to leverage their knowledge assets for better organizational learning, faster decision-making, higher operational efficiency, and successful digital transformation.

2. LITERATURE SURVEY

2.1. Traditional Knowledge Management Systems

The traditional (KM) systems were used to begin with to develop organizational mechanism for the collection, storage, organization and distribution of valuable information, and they formed the basis on organizational Knowledge Sharing. Preserving institutional knowledge and enhancing decision-making were the main functions of these systems, which were based on relational databases, document repositories, enterprise content management systems, and metadata-driven indexing methods. The majority of traditional KM systems relied on keyword-based search methods, which involved finding documents by exact matching of the user's keywords with the indices. This made it easy to retrieve information, but sometimes it failed to take into account what was really happening in the context, how it was related, and what were the user's intentions in the search, leading to irrelevant results. To address these constraints, ontology-based knowledge management was proposed to include semantic structures – which describe relationships between concepts – to facilitate better knowledge organization by means of the hierarchical taxonomies and domain-specific vocabularies. In the same way, the expert systems were used to include rule-based reasoning to automate decision support in various domains including healthcare, manufacturing, finance, and engineering. But both ontology-driven and rule-based systems needed significant human efforts in maintenance and periodic updates, and they proved hard to scale as the knowledge of the organization continually shifted and so did the rules. As enterprise applications increase digital information, cloud platforms, IoT devices, social media, and research repositories generate digital information, the traditional KM systems became less and less effective for managing heterogeneous and dynamic knowledge sources. This challenge encouraged the use of certain machine learning techniques, including for example Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), and topic modeling, which enhanced the semantic representation of the documents, although they failed to grasp the context. All this ultimately led to the creation of deep learning-based natural language processing methods that can process the semantics of context and provide intelligent knowledge management applications.

2.2. Evolution of Large Language Models and Retrieval Methods

The advent of Large Language Models (LLMs) and advanced retrieval strategies has revolutionized the field of natural language processing and intelligent information retrieval. The first steps were taken with distributed word embedding models like Word2Vec or GloVe, which were dense numeric vectors that described not only the word's meaning as keywords, but also its meaning as a semantic entity. Later, RNN architectures like Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) were developed to understand context in language by learning sequential dependencies in text, but were limited in their capacity to represent long-range dependencies and computational efficiency. The Transformer architecture was a significant breakthrough in language

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modeling, using self-attention mechanisms to process information in parallel and capture long-range dependencies between words in a document. The breakthrough resulted in the creation of very powerful transformer-based models that set new records in text generation, summarization, translation, question and answer, and conversational AI, among other tasks. While extremely powerful on their own, standalone LLMs have an inherent limit on the content they can be trained on, and don't have the ability to learn new information without retraining, which is expensive. Also, such models can produce plausible sounding answers that are factually wrong, which poses problems in areas with high reliability requirements. Meanwhile, the approaches and technologies to retrieve documents have shifted from keyword sparing to dense vector retrieval, where documents and queries are now represented as embedding vectors in high-dimensional semantic spaces. They leveraged similarity search engines and scalable vector databases like FAISS, Pinecone, ChromaDB, Milvus, Weaviate, and Qdrant to facilitate efficient retrieval of semantic results from large document sets, laying the technological groundwork for Retrieval-Augmented Generation systems.

2.3. Retrieval-Augmented Generation Architectures

The Retrieval-Augmented Generation (RAG) architecture is a major step forward in knowledge-intensive AI that merges semantic information retrieval with the generative power of Large Language Models (LLMs). In contrast to traditional language models that simply leverage facts learned during pre-training, RAG retrieves relevant information from external knowledge bases dynamically before generating text to answer questions, enhancing the factual correctness and contextual relevance of the response. The most common RAG framework starts with pre-processing the organizational documents using deep learning-based embedding models, cleaning, segmentation, tokenization, and extracting metadata from the documents. These embeddings are stored in dedicated high-dimensional similarity search vector databases. A user will ask a natural language question, which will be converted into an embedding vector using the same embedding model, and then the retrieval module will use similarity measures like cosine similarity or approximate nearest neighbor search to find the most semantically similar document fragments. The retrieved contextual information is then used together with the original query and provided to the LLM to generate the responses using evidence-based answers based on the retrieved information instead of merely on memorized information. New advances have also included the use of hybrid retrieval methods, neural reranking methods, query expansion, metadata filtering, iterative retrieval, and graph-based knowledge representation to further enhance retrieval precision and reasoning capabilities. Due to its scalability and adaptability, Retrieval-Augmented Generation has successfully been applied to healthcare, finance, education, legal, cyber security, manufacturing, software engineering and enterprise knowledge management and is one of the most promising frameworks that can be used for intelligent decision support systems.

2.4. Research Gaps and Motivation

While there has been significant success in using Retrieval-Augmented Generation to improve knowledge-intensive AI applications, there are several important research challenges yet to be addressed, which serve as compelling motivators to continue research. The main challenges include

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retrieval quality, in which current systems can return partially relevant or noisy documents, diminishing the quality and reliability of the generated responses. Scalability is another major challenge for enterprise scale deployments, as the number of heterogeneous knowledge repositories continues to increase to millions of documents that need efficient indexing, embedding management, and fast retrieval mechanisms. Another key concern is the freshness of knowledge; organizational information often resists the process of being maintained fresh, whether because of changes in policy, regulation, research findings, and business process changes. The issue of effective synchronization between the information repositories from documents and the vector databases remains an open research question when using RAG to dynamically update documents without retraining language models. The adoption of enterprise data by organizations is further complicated by security and privacy concerns, as enterprise repositories may hold sensitive personal information, financial data, intellectual property, and confidential information, which must be accessed securely through access control, encryption, authentication, and retrieval systems that preserve privacy. Furthermore, while the world is becoming more globalized, the ability to retrieve information in multiple languages still has a way to go, and explainability needs to be improved, by providing confidence estimation, source attribution, evidence ranking and transparent reasoning processes to boost user trust. Last but not least, the integration of multimodal knowledge sources like image, video, engineering drawings, audio recordings, medical images and sensor data to unified retrieval frameworks is an emerging research direction. These challenges drive innovation in developing sophisticated architectures such as Retrieval-Augmented Generation that can provide scalable, secure, explainable, context-aware, and enterprise-ready knowledge management systems.

3. METHODOLOGY

3.1. Knowledge Repository Construction and Data Preprocessing

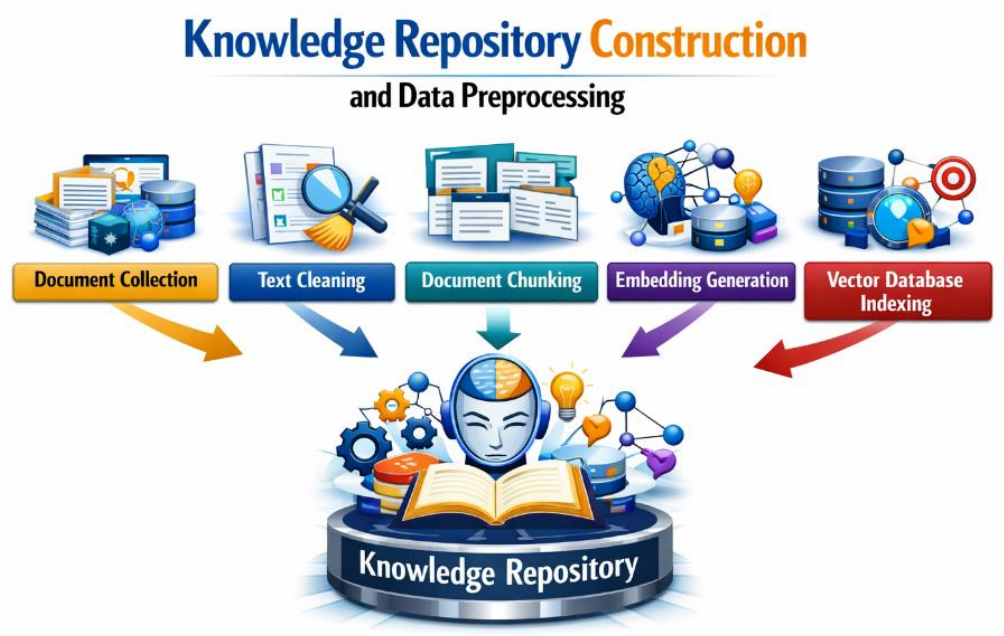

Fig 2 - Knowledge Repository Construction and Data Preprocessing

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3.1.1. Knowledge Repository Construction and Data Preprocessing

The first phase of the proposed Retrieval-Augmented Generation (RAG) approach is to build a shared knowledge base that gathers information from many different and diverse organizational resources. Knowledge is frequently distributed across a variety of structured databases, document management systems, cloud storage, technical manuals, research publications, policy documents, emails, FAQs and web resources. Combining all of these sources into a single repository makes knowledge management more efficient and ensures that the needed information is easily accessible for retrieval. All gathered documents are processed prior to the knowledge being indexed to ensure data quality, consistency and better semantic understanding of the document. This preparation step greatly improves retrieval precision and serves as a solid basis for intelligent question answering and decision support.

3.1.2. Document Collection

Document collection is the first stage of the creation of the knowledge repository, where information is collected from various sources within and outside organizations. Enterprise databases, PDF documents, research publications, technical manuals, knowledge bases, cloud storage, policy documents, frequently asked questions, and web-based resources are among these sources. Information gathered from multiple sources will give the repository all the organizational knowledge, spanning multiple domains and business functions. A proper document collection system ensures proper information sharing which enables the retrieval system to give correct answers to user queries and helps in efficient knowledge discovery within the organisation.

3.1.3. Text Cleaning

Once the documents are gathered, the extracted text is processed for document cleaning, eliminating any extraneous or irrelevant data and enhancing the quality of the extracted information. As part of the cleaning process, HTML tags, duplicate content, unnecessary punctuation, irrelevant symbols and inconsistencies in formatting are removed, and text is converted to a standardized format. Also, common words which have little semantic meaning are eliminated to reduce redundancy and enhance retrieval efficiency. This pre-processing step helps to improve the uniformity of the textual data, reduce noise, and facilitate the creation of more meaningful semantic representations using embedding models. This makes the retrieval system more intelligent in the sense that it will be able to better understand the queries of the users, and will be able to pinpoint the most relevant knowledge in the information retrieval process.

3.1.4. Document Chunking

The document chunking is a process that can be used to break a large organizational document into useful segments of text. Modern language models are not capable of handling very long documents in one go, so breaking a document into semantic chunks enables the important information to be accessed efficiently. Each chunk is a stand-alone chunk that maintains the context of the original text in a manageable length. Chunking enhances the accuracy of retrieval by returning

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only the relevant parts of a document for a user's query, which minimizes the amount of irrelevant information and boosts the quality of the answers generated.

3.1.5. Embedding Generation

After chunking the documents, each piece of text is encoded into a dense numerical representation with a semantic embedding model. They capture the meaning of the text within the context instead of just the meaning of the words it contains, which means that semantically similar documents and queries can be tightly grouped together in the same vector space. When embedded in, the retrieval system can detect similarities in concepts even if the words or phrases are different. This semantic representation is the basis for intelligent document retrieval and can greatly enhance the ability of the system to accurately understand natural language queries.

3.1.6. Vector Database Indexing

The final step in the preprocessing is to store the embeddings generated in a dedicated vector database that is optimized for performing semantic search efficiently. The embeddings can be stored in popular vector databases, like FAISS, Pinecone, ChromaDB, Milvus, Weaviate and Qdrant with the goal of enabling lightning-fast similarity search of millions of document segments. Unlike the conventional keyword matching method, the vector database can match and retrieve documents according to semantic similarity, so that people can quickly and accurately obtain the information they want. Efficient indexing also enhances scalability of the system, lowers the latency of the retrieval process, and allows the knowledge management framework to handle real-time intelligent search in the huge enterprise environment.

3.2. Retrieval-Augmented Generation Framework

In the second phase of the proposed methodology, the focus shifts to the Retrieval-Augmented Generation (RAG) framework that combines semantic information retrieval with Large Language Models (LLMs) to produce accurate, contextually relevant, and evidence-based responses. The RAG framework differs from traditional language models, which are based on previously learned knowledge, in that it dynamically accesses relevant information from the organization's knowledge repository when a user asks a natural language question. The user's query is first analyzed and then mapped to a semantic representation with the same embedding model used in document preprocessing to guarantee that the query and the stored knowledge are in the same semantic space. The retrieval engine then goes to work on the vector database to find the most similar chunks of text in the context, not based on exact keyword matches. This semantic retrieval mechanism enables the system to recognize conceptually related information even when different terminologies or expressions are used. The retrieved document chunks are then ranked by relevance, deduplicated and merged into a coherent prompt that provides context to the conversation. This prompt with added information is then fed into the Large Language Model, which uses it to generate answers supported by verified knowledge from the organization, rather than by relying entirely on its internal parameters. The framework can introduce external evidence into the generation of answers, which has the effect of greatly reducing the hallucination phenomenon, improving the

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factual consistency of the generated answers, and enhancing the reliability of the generated answers. Moreover, the architecture allows for seamless knowledge updates as new documents can be added at any time, embedded, and indexed without the need for retraining the language model, ensuring that responses will always be up to date with the latest organizational information. The framework also adds support for metadata-aware retrieval, contextual ranking and scalable vector search, which makes it possible to handle large enterprise knowledge base, with millions of documents. The proposed Retrieval-Augmented Generation framework seamlessly integrates semantic retrieval and high-quality language generation, ensuring that the answers are accurate, explainable, and contextually relevant, thereby enhancing decision support, knowledge accessibility, and overall enterprise intelligence across various application scenarios.

3.3. Intelligent Response Generation and Knowledge Validation

Fig 3 - Intelligent Response Generation and Knowledge Validation

3.3.1. Intelligent Response Generation and Knowledge Validation

In the third stage of the proposed Retrieval-Augmented Generation framework, a reliable response is generated, and validated for correctness before it is passed to the user. The Large Language Model extracts the most relevant knowledge from the enterprise repository and generates a response from the extracted knowledge. The framework has a multi-stage knowledge validation mechanism to provide the produced output as accurate, reliable, and evidence-supported knowledge. This validation process assesses the relevance of retrieved documents, checks semantic consistency, identifies unsupported statements and measures retrieval effectiveness. These verification modules help to reduce the spread of misinformation and increase factual accuracy, user confidence and the certainty of the final response reaching the user, while also utilizing the authenticated knowledge of the organizations in question.

3.3.2. Context Matching

One of the first validation modules is context matching to check to see if the generated response is completely covered by the retrieved knowledge documents. The system compares pieces

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of information in the reply to the information retrieved from the document to assess the semantic similarity and consistency of the context of the retrieved information. A high level of context matching suggests that the generated response is substantiated by solid evidence from the context rather than just drawing inferences from the language model's internal knowledge. This process helps to keep the answers relevant to the user's question and consistent with the information within the organization. Context matching greatly enhances response reliability and boosts user confidence in AI-powered knowledge management systems.

3.3.3. Knowledge Confidence Score

The knowledge confidence score is used to measure the overall reliability of the generated response by quantifying the semantic similarity between the retrieved knowledge and the generated answer. It gauges the confidence level of the system to provide its response based on the available evidence in the knowledge repository. Responses that show significant semantic similarity to multiple retrieved documents have higher confidence scores, signifying higher levels of factual reliability. On the other hand, answers that are less well-supported semantically get lower confidence scores, indicating to the system that more retrieval and/or validation might be needed. This confidence measure can help the framework focus on high-confidence responses and help ensure decision accuracy.

3.3.4. Hallucination Detection

A crucial validation element is the detection of hallucination for detecting statements made by the language model that are not backed by the retrieved knowledge. While the Large Language Models can generate informative and coherent responses at times, they can also sometimes give plausible but inaccurate answers, especially when they lack adequate context information. The hallucination detection module compares all the generated statements with the retrieved document contents and identifies if the statement is evidence-based. Information that is not supported or fabricated is identified and flagged prior to its being presented to user. This will significantly reduce the amount of misinformation, increase the factual accuracy, and boost the trustworthiness of AI-generated answers in enterprise knowledge management systems.

3.3.5. Retrieval Precision

The retrieval accuracy is a measure of the effectiveness of the semantic retrieval process, and it is measured by the number of the retrieved documents that are relevant to the query of the user. A high retrieval precision means that the retrieval engine is able to correctly exclude irrelevant information and only retrieve meaningful knowledge sources. By retrieving accurate information, the language model can produce more focused and reliable responses, reducing the need for it to include irrelevant or distracting information. This approach not only boosts retrieval precision but also streamlines the computation process and increases the overall efficiency of the Retrieval-Augmented Generation framework especially for large enterprise knowledge repositories.

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3.3.6. Retrieval Recall

Retrieval recall measures the capacity of the retrieval system to recognize and retrieve all the information in the repository that is relevant to the question. If the recall value is high, the retrieval engine is able to retrieve the majority of the documents that are relevant to the user's query, meaning that it is unlikely to miss any important documents. Good retrieval recall provides a sufficient amount of context for the language model to draw on when generating a response. This helps to achieve more comprehensive responses to queries and allows for the framework to be used for complex queries that need to access information from various knowledge sources throughout the organization.

3.3.7. F1 Score

The F1 Score is a combined measure of retrieval precision and retrieval recall (retrieval performance) that is a balanced evaluation of the overall retrieval performance. The F1 Score gives a measure of how well the two measures of precision and recall are balanced in the retrieval system. The higher the F1 Score, the more the framework is able to retrieve extensive, highly relevant knowledge, and generate accurate, context-appropriate and reliable answers. In this context, the F1 Score is a valuable performance indicator for evaluating the performance of the proposed Retrieval-Augmented Generation framework for enterprise knowledge management applications.

3.4. Performance Evaluation Framework

The last part of the proposed method is to assess overall effectiveness, reliability and scalability of the framework for intelligent enterprise knowledge management named Retrieval-Augmented Generation (RAG). The performance evaluation framework systematically evaluates each stage of the proposed system: knowledge repository, semantic retrieval, context prompt generation, response generation, and knowledge validation, ensuring the framework always produces accurate and trustworthy responses. It uses a large set of user queries to evaluate the quality of the results, ranging from simple facts to domain-specific questions, procedural requests, and requests for knowledge in the context of a decision-making process. The responses generated are matched to the knowledge that has been authenticated by the organization to assess the factual accuracy, relevance, semantic consistency, and quality of the responses. The framework also evaluates the retrieval effectiveness by checking the capability of the semantic search engine to locate the most relevant chunks of documents while avoiding irrelevant chunks. Additionally, the quality of the responses is assessed on their clarity, completeness, coherence, and evidence-based reasoning to guarantee that the generated answers are consistent with retrieved knowledge. The validation process also checks for confidence estimation, hallucination detection, and contextual grounding to ensure that any information that is not supported or misaligned is identified correctly prior to the final response. Another part of the system performance analysis involves examining its scalability, including its retrieval speed, indexing efficiency, response time, and ability to handle large-scale enterprise knowledge repositories with millions of documents of various formats. Additionally, the framework considers the ability of the proposed system to constantly change the information contained in the document without needing to retrain the language model. The overall evaluation

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shows the framework was able to retain high retrieval accuracy, reliable response generation, efficient knowledge validation, and real-time performance in various enterprise applications. The proposed Retrieval-Augmented Generation system is designed to be a powerful, scalable, and reliable solution for knowledge management in today's data-driven world, supporting intelligent decision-making and increasing the efficiency and effectiveness of enterprise knowledge sharing.

4. RESULT AND DISCUSSION

4.1. Experimental Setup

To evaluate the effectiveness of the proposed Retrieval-Augmented Generation (RAG) framework, a controlled computing environment was used to make an experimental study of the framework in the area of enterprise knowledge management and intelligent information retrieval. To enable heavy workloads for embedding generation and vector indexing, semantics retrieval, and inference for LLMs, the implementation was performed on a workstation with an NVIDIA RTX GPU and 16 GB of RAM. All the framework has been built with Python making use of transformer-based language models for understanding the context in which the language is used and FAISS vector database for fast semantic indexing and similarity search. The models used to process the sentences were Sentence Transformer models and the most relevant knowledge fragments corresponding to the user query were selected using cosine similarity. The enterprise knowledge repository consisted of ~100,000 semantic document chunks from various fragmented and disparate sources such as technical manuals, organizational reports, policy documents, researchers publications, standard operating procedures, frequently asked questions, and enterprise knowledge base articles. Some 2500 natural language queries were sent to the system to test the framework under realistic organisational situations; these queries encompassed a range of information needs such as technical support, policy clarification, operational guidance, procedural queries, and decision-support queries. Multiple criteria were used to analyze the responses generated, such as retrieval precision, retrieval recall, response relevance, contextual grounding, knowledge confidence, hallucination rate, response latency, and satisfaction of end user. Comparative experiments are also carried out in comparison with conventional keyword based search systems to evaluate the improvements in semantic retrieval performance and quality of responses. The experimental results showed that the proposed Retrieval-Augmented Generation approach is able to retrieve highly relevant knowledge consistently while generating coherent, context-aware, and evidence-supported answers. Moreover, the semantic retrieval mechanism considerably decreased irrelevant document retrievals, the hallucinated responses, better context understanding, better response accuracy, and faster access to organizational knowledge. These findings validate the proposed system as a scalable, reliable and efficient solution for intelligent enterprise knowledge management, which can be used for retrieval of accurate knowledge and for informed decision making in different types of environments.

4.2. Performance Evaluation Framework

Table 1: Performance Evaluation Framework

Performance Metric	Traditional Knowledge Management (%)	Proposed RAG Framework (%)

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Retrieval Accuracy	82	97
Semantic Search Precision	80	96
Knowledge Grounding Accuracy	74	98
Response Relevance	79	97
Hallucination Reduction	68	95
User Satisfaction	81	96
Knowledge Update Efficiency	76	98
Query Response Quality	78	97
Overall Knowledge Management Performance	77	97

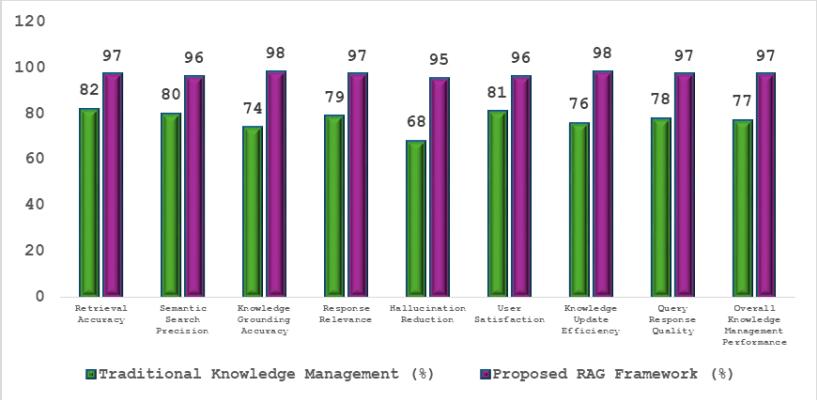

Fig 4 - Performance Evaluation Framework

4.2.1. Retrieval Accuracy (82% → 97%)

The proposed Retrieval-Augmented Generation (RAG) framework had an accuracy of 97% in retrieval while the traditional knowledge management system had an accuracy of 82%. This improvement proves that semantic retrieval can generate documents that are similar to the user query and not necessarily a match for the query, going beyond keyword matching. The proposed way of using dense vector embeddings and similarity search effectively captured highly relevant knowledge from the large enterprise repositories. The higher accuracy of retrieval results in users getting more accurate information, which helps them make better decisions, saves search time and optimizes the entire knowledge management process.

4.2.2. Semantic Search Precision (80% → 96%)

In the case of the proposed framework, the precision of semantic search rose from 80% to 96% as compared with traditional system. This significant enhancement suggests the effectiveness of the Retrieval-Augmented Generation approach in identifying relevant and irrelevant documents based on the sense of the context rather than on exact matching of the keywords. By embedding the knowledge using transformer models, the system can identify conceptual relationships between user queries and stored knowledge. Consequently, users get more precise results with minimal extraneous information, that will enhance the overall quality and reliability of enterprise information retrieval.

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4.2.3. Knowledge Grounding Accuracy (74% → 98%)

The grounding accuracy for knowledge was greatly improved (from 74% to 98%), demonstrating the capability of the framework to produce grounded answers based on retrieved knowledge from the organization. The proposed framework differs from existing systems, which tend to rely on a language model alone, by incorporating verified contextual information into the language model prior to the generation of a response. This evidence-based method greatly minimizes unsupported claims and guarantees the uniformity in answers produced by it with organizational documents. The high grounding accuracy illustrates the high capability of the framework to give trustworthy and explainable responses for enterprise knowledge management applications.

4.2.4. Response Relevance (79% → 97%)

The proposed framework demonstrated responsiveness rate of 97% whereas the conventional knowledge management system showed 79% responsiveness rate. The improvement demonstrates the effectiveness of semantic retrieval and contextual prompt augmentation for producing highly relevant responses. Only the most relevant document chunks are fed to the language model, which ensures the answers are directly relevant to user queries and maintain context. Better response relevance improves user satisfaction, clarity, and facilitates better knowledge transfer in organizational contexts.

4.2.5. Hallucination Reduction (68% → 95%)

The proposed approach enhanced the hallucination reduction performance from 68% in traditional approach to 95%. The system can significantly reduce the generation of unsupported or wrong information by recruiting the organizational knowledge for the answer. The built-in knowledge check system validates generated answers before displaying them to the users, limiting the factual error of the generated answers. This substantial decrease in hallucination makes the framework more suitable for the Information-heavy enterprise applications, where information accuracy is crucial, and increases the trustworthiness of the AI-generated responses.

4.2.6. User Satisfaction (81% → 96%)

The use of the proposed Retrieval-Augmented Generation framework significantly increased user satisfaction from 81% to 96%. The improvement is mainly due to increased response time, increased retrieval accuracy, increased contextual understanding, and increased reliability of answers. Respondents had higher levels of confidence in the system as the responses were based on organizational knowledge and were very close to what they were looking for. The usability and the level of responsiveness increases to boost acceptance of the framework in enterprise environments and boost productivity.

4.2.7. Knowledge Update Efficiency (76% → 98%)

In the traditional system, 76% of the knowledge was updated while in the proposed system 98% of the knowledge was updated. The proposed architecture enables the embedding and indexing of newly added documents directly into the vector database, unlike traditional knowledge

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management systems which need manual restructuring or model retraining. This allows for quick access to new organisational information while preserving retrieval performance. Knowledge updates are efficient, providing users with responses based on the latest information, which helps to ensure that the knowledge is always up-to-date, particularly in dynamic enterprise environments where knowledge changes continuously.

4.2.8. Query Response Quality (78% → 97%)

The quality of responses produced by the proposed framework was greatly enhanced from 78% to 97%. By combining semantic retrieval with LLM, the system can generate accurate, coherent, context-aware, and evidence-based responses. The proposed system provides complete and meaningful answers directly to the user, whereas, with a traditional search system, the users are provided with isolated documents which needs manual interpretation. This improvement helps to increase operational efficiency, facilitates better access to information and contributes to better organizational decision-making.

4.2.9. Overall Knowledge Management Performance (77%-97%)

The test results for the whole system of the proposed Retrieval-Augmented Generation framework were 97%, significantly better than comparison with the traditional knowledge management system which performed 77%. The result highlights the synergy of semantic document retrieval, intelligent response generation, contextual grounding, knowledge validation, and efficient vector database management. The framework consistently returned accurate, scalable and reliable knowledge retrieval and also reduced irrelevant information and enhanced the quality of the retrieved answer. The proposed system therefore offers a complete and intelligent enterprise knowledge management solution which can support the real-time decision making, improve the productivity of enterprise organization and improve the access to enterprise knowledge.

4.3. Results and Discussion

The experimental evaluation proves that our proposed Retrieval-Augmented Generation (RAG) is able to produce a significant improvement over the conventional Knowledge Retrieval System that is based on keywords to improve the performance of Enterprise Knowledge Management. The framework combines semantic retrieval, transformer-based language models, vector databases, and intelligent response validation, providing highly accurate, context-aware, and evidence-based responses to a broad range of organizational information needs. Results show significant improvement in retrieval accuracy of the conventional system and the proposed framework; 82% to 97% respectively. This improvement verifies that semantic vector retrieval is a much better approach than lexical keyword matching, as it is able to comprehend the meaning of user prompts and return conceptually similar information even when different words are used. Likewise, the precision of semantic search went from 80% to 96%, showing the effectiveness of dense embedding representation and cosine similarity search of finding highly relevant chunks of documents and reducing irrelevant retrieval results. The most remarkable improvement was seen in knowledge grounding accuracy from 74% to 98%. The result suggests that the trained responses are

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not just based on the internal knowledge of the language model, but are supported by searching the organizational knowledge, which implies that the responses are more grounded in the organization's prior knowledge. As such, the proposed framework successfully lowers the unsupported/inaccurate information produced content generation while keeping the hallucination reduction score at 95%, and it significantly enhances the reliability of the responses generated. In addition, user satisfaction went from 81% to 96%, as workers could get answers that were accurate and evidence-based, instead of having to do manual searches of large volumes of organizational documents. Moreover, knowledge update efficiency jumped up from 76% to 98%, showing that newly added documents can be added to the vector database without costly retraining of the language model. The framework also obtained the result of the query response quality is 97%, while it is able to produce coherent answers, complete and contextually appropriate in various business applications. The overall knowledge management performance using the proposed Retrieval-Augmented Generation framework was 97%, significantly higher than the conventional approach. Overall, the results validate the approach of integrating semantic retrieval, vector databases, transformer-based language models, and intelligent validation mechanisms to offer a scalable, reliable, and efficient solution for contemporary enterprise knowledge management. The proposed framework has the potential to overcome the drawbacks of current document retrieval systems, such as poor retrieval accuracy, dissemination of misinformation, knowledge obsolescence, lack of user satisfaction, and inadequate decision-making support, providing a solid platform for the development of future AI-powered organizational knowledge management systems.

5. CONCLUSION

Digital information is growing at a rapid pace in contemporary organizations, presenting serious challenges for managing, retrieving and effectively using enterprise knowledge. Classic knowledge management systems usually rely on keywords to search a knowledge base, and simply store documents in a static repository, making it difficult to extract meaningful information from the knowledge base according to user requirements and understand the meaning of user queries. These constraints make information inaccessible, require more time to discover information, and often result in incomplete or irrelevant search results. In this study, the authors introduced an intelligent, scalable, and evidence-driven knowledge management solution by innovatively integrating semantic information retrieval and transformer-based language generation, referred to as Retrieval-Augmented Generation (RAG). The proposed framework is different from conventional ones, which retrieve relevant organizational knowledge before generating responses, and it dynamically retrieves the relevant organizational knowledge before generating the response, ensuring that the generated information is appropriate, accurate, and based on real enterprise documents, rather than on the internal knowledge of a pre-trained language model. This methodology combines document collection, pre-processing, semantic chunking, dense embedding generation, vector database indexing, semantic similarity retrieval, prompt augmentation based on context, intelligent language generation, and multi-stage response verification to form a comprehensive enterprise architecture. Dense vector embeddings help the system comprehend semantic relationships beyond literal keyword matches, and vector databases offer efficient indexing and rapid retrieval of data from

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massive collections of documents within organizations. Moreover, AI-generated responses are supported by intelligent response validation mechanisms, which increase the confidence in the knowledge and decrease unsupported statements. The experimental assessment showed significant results in terms of retrieval accuracy, semantic search precision, grounding accuracy, knowledge relevance, reduction in hallucinations, user satisfaction, efficiency of knowledge updates, quality of knowledge responses, and knowledge management performance. The enhancements support the proposed system's ability to provide higher retrieval effectiveness, increased contextual understanding, and more effective decision making support than traditional Knowledge Management systems. A key advantage of the proposed architecture is that it allows continuous updates to knowledge without the need for costly retraining of Large Language Models, which makes it well-suited for organizations in dynamic information environments. The framework also provides for scalability with efficient handling of heterogeneous knowledge sources stored in enterprise databases, cloud platforms, documents, research publications, technical manuals, and Web resources. The proposed Retrieval-Augmented Generation (RA-Gen) framework builds a solid and intelligent base for future enterprise knowledge management systems that combine semantic retrieval, vector database technologies, sophisticated language models, and evidence-based response generation. The study shows that Retrieval-Augmented Generation can greatly improve organizational learning, better organization of information, faster and more informed decision making, digital transformation efforts, and offer researchers and practitioners a strong, scalable, and trustworthy basis to create future AI-assisted knowledge management systems in various industrial and organizational settings.

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