International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802051

Customizable Retrieval-Augmented Generation Framework for Domain-Specific Intelligent Systems

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Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: The widespread adoption of Large Language Models (LLMs)has enabled significant advances in automated knowledge systems, yet their application to specialized domains remains challenging due to hallucinations, lack of domain-specific context, and limited customization capabilities. This pa per presents a novel customizable Retrieval-Augmented Generation (RAG) framework that enables users to construct domain-specific intelligent systems tailored to their unique requirements. Un like traditional RAG implementations that rely on fixed knowledge bases and retrieval mechanisms, our framework provides a modular architecture allowing users to upload custom datasets, configure embedding models, define retrieval strategies, and establish evaluation metrics. The system com bines user-defined knowledge repositories with state-of-the-art retrieval techniques and language models to generate contextually accurate, domain-specific responses in real-time. We implement advanced data chunking strategies, multilingual BERT-based vectorization, and comprehensive evaluation metrics including faithfulness, answer relevancy, context recall, and context precision. Experimental validation across educational, healthcare, and analytical domains demonstrates significant improvements in response quality, with faithfulness scores of 0.7044, answer relevancy of 0.9838, and context precision of 0.8756 using GPT-4o mini, substantially outperforming generic LLM approaches. Our customizable framework addresses critical limitations of existing systems by providing users with complete control over knowledge integration, retrieval mechanisms, and response generation, paving the way for democratized AI system development across diverse domains.

KEYWORDS: Retrieval-Augmented Generation, Customizable AI, Knowledge Base Integration, Vector Embeddings, Domain-Specific Agents, LLM Fine-Tuning, Context Retrieval, AI Evaluation Metrics

I. INTRODUCTION

The advent of Large Language Models (LLMs) such as GPT-4, Claude, and Gemini has revolutionized natural language processing, enabling sophisticated conversational AI systems across numerous domains. However, deploying these models for specialized applications presents significant challenges: they frequently generate hallucinated information, lack domain-specific knowledge beyond their training cut off dates, and cannot easily incorporate proprietary or specialized datasets without expensive fine-tuning processes [1, 11].

Retrieval-Augmented Generation (RAG) has emerged as a promising paradigm to address these limitations by augmenting LLM capabilities with external knowledge retrieval [7]. Traditional RAG systems retrieve relevant documents from a knowledge base and provide them as context to the LLM, significantly improving factual accuracy

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and enabling access to up-to-date information. However, ex isting RAG implementations typically offer limited customization options, requiring users to adapt their needs to pre-configured systems rather than configuring systems to match their specific requirements.

This paper introduces a novel customizable RAG framework that fundamentally shifts this paradigm by empowering users to construct domain-specific intelligent systems aligned with their unique knowledge domains, retrieval preferences, and evaluation criteria. Our framework provides a comprehensive toolkit enabling users without deep machine learning expertise to:

- Upload and integrate custom knowledge repositories in various formats (PDFs, documents, structured data)
- Configure data processing pipelines including chunking strategies and preprocessing rules
- Select and customize embedding models for optimal domain-specific vectorization
- Define retrieval mechanisms and similarity metrics tailored to their use cases
- Establish domain-appropriate evaluation metrics and quality thresholds
- Deploy conversational interfaces powered by their customized RAG system

MOTIVATION AND CONTRIBUTIONS

The motivation for this work stems from observing the disconnect between the potential of RAG systems and their practical deployment in specialized domains. Educational institutions struggle to create inter active learning assistants aligned with specific curricula; healthcare providers need HIPAA-compliant systems trained on proprietary medical knowledge; research organizations require tools that understand domain-specific terminology and concepts. Each domain demands customization that current fixed architecture RAG systems cannot easily provide.

Our key contributions are:

1. Modular Architecture: A flexible framework supporting customization at every stage of the RAG pipeline, from data ingestion to response generation.

2. Multi-Strategy Data Processing: Implementation of multiple chunking strategies (fixed-size, context-aware, recursive, semantic) with configurable parameters.

3. Multilingual Support: Integration of multilingual BERT for cross-lingual knowledge retrieval and response generation.

4. Comprehensive Evaluation: Implementation of RAGAS metrics [3] including faithfulness, answer relevancy, context recall, and context precision.

5. Comparative Analysis: Systematic evaluation across multiple LLMs (GPT-4, GPT-4o mini, Gemini 1.5) demonstrating framework effectiveness.

6. Real-World Validation: Deployment and testing in educational domain demonstrating practical applicability.

The remainder of this paper is organized as follows: Section 2 reviews related work in RAG systems and customizable AI frameworks. Section 3 details our system architecture and implementation. Section 4 presents our experimental methodology and results. Section 5 discusses implications and limitations, and Section 6 concludes with future directions.

II. RELATED WORK

2.1 Retrieval-Augmented Generation

The RAG paradigm was formalized by Lewis et al. [7], who demonstrated that augmenting sequence-to sequence models with retrieval mechanisms significantly improved performance on knowledge-intensive 2 tasks. This seminal work established the foundation for combining parametric memory (the LLM's weights) with non-parametric memory (retrieved documents).

Recent advances have explored various aspects of RAG systems. Gao et al. [4] provided a comprehensive survey of RAG architectures, categorizing approaches based on retrieval methods, integration strategies, and generation techniques. Parnami and Lee [9] investigated few-shot learning approaches for RAG, enabling efficient adaptation to new domains with limited examples.

2.2 Vector Databases and Embeddings

The effectiveness of RAG systems heavily depends on the quality of document embeddings and retrieval mechanisms. Kukreja et al. [6] reviewed vector databases and embedding techniques, highlighting the importance of choosing appropriate similarity metrics and indexing strategies for different applications. Devlin et al. [2] introduced BERT,

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which revolutionized text representation through bidirectional trans formers, forming the basis for many modern embedding models.

2.3 Rag Evaluation and Optimization

Evaluating RAG systems presents unique challenges distinct from traditional NLP tasks. Es et al. [3] introduced the RAGAS framework for automated RAG evaluation, defining metrics that assess both retrieval quality (context precision, context recall) and generation quality (faithfulness, answer relevancy). These metrics have become widely adopted for RAG system assessment.

Recent work has explored hybrid approaches to RAG optimization. Omrani et al. [8] proposed combining dense and sparse retrieval methods to improve recall. Selva Kumar et al. [10] investigated strategies for addressing LLM hallucinations in RAG systems through improved retrieval precision.

2.4 Customizable AI Frameworks

While numerous RAG implementations exist, few provide comprehensive customization capabilities. Joshi et al. [5] developed a multi-modal RAG pipeline for documents containing text, tables, and images, but with limited user configurability. White et al. [12] explored prompt patterns for enhancing ChatGPT interactions, suggesting the importance of user control over AI system behavior.

Our work distinguishes itself by providing end-to-end customization capabilities while maintaining ease of use, enabling domain experts without deep ML knowledge to construct sophisticated RAG systems.

III. SYSTEM ARCHITECTURE

Our customizable RAG framework comprises six main components: Data Ingestion, Processing Pipeline, Vectorization, Storage, Retrieval, and Generation. Each component offers multiple configuration options enabling users to tailor the system to their specific requirements.

3.1 Data Ingestion and Extraction

The framework supports multiple document formats through a flexible ingestion pipeline:

OCR Processing: For PDF documents,we employ Optical Character Recognition to extract machine readable text. We integrate LlamaParse for advanced extraction of complex elements including tables, figures, and multi-column layouts.

Multilingual Support: The system automatically detects and processes documents in multiple languages, storing content with language metadata for optimized retrieval.

Metadata Extraction: Beyond raw text, we extract structural metadata including:

- Document hierarchy (sections, subsections, paragraphs)
- References and citations
- Tables and figures with captions
- Author information and publication dates

3.2 Configurable Processing Pipeline

Users can configure the data processing pipeline through a declarative interface specifying chunking strategy, chunk size, overlap parameters, and preprocessing rules.

3.2.1 Chunking Strategies

We implement four distinct chunking approaches:

1. Fixed-Size Chunking: Divides text into chunks of predetermined token count with configurable overlap. Simple and efficient, suitable for homogeneous documents.
2. Context-Aware Chunking: Respects document structure, creating chunks at natural boundaries (sentence, paragraph, or section breaks). Preserves semantic coherence at the cost of variable chunk sizes.
3. Recursive Chunking: Hierarchically subdivides large chunks that exceed size thresholds.
Balances size constraints with context preservation.
4. Semantic Chunking: Uses embedding similarity to group semantically related sentences. Maximizes within-chunk coherence but computationally intensive.

Our default configuration employs LlamaIndex's sentence splitter with 512-token chunks and 128 token overlap, balancing context preservation with retrieval precision. Users can adjust these parameters based on their domain characteristics.

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3.2.2 Text Preprocessing

Configurable preprocessing includes:
• Noise removal (special characters, formatting artifacts)
• Normalization (case folding, Unicode standardization)
• Language-specific processing (stemming, lemmatization)
• Custom regex-based transformations

3.3 Vectorization and Embedding

The framework employs multilingual BERT (mBERT) as the default embedding model, with support for user-provided custom models. mBERT's transformer architecture with self-attention mechanisms captures nuanced semantics across 104 languages.

Embedding Process: Each text chunk is encoded into a dense vector representation v ∈ Rd where d ∈{768,1536}depending on model configuration. The embedding function f : Text → Rd transforms textual content into geometric space where semantic similarity corresponds to vector proximity.

Node Structure: Embeddings are stored as nodes with associated metadata:

```
{
  "_id": "chunk_001",
  "text": "Organisms that convert decaying...",
  "vector": [0.23, 0.89, -0.10, 0.54, ...],
  "metadata": {
    "source": "biology_textbook.pdf",
    "chapter": 3,
    "subject": "ecology",
    "language": "en"
  }
}
```

This enriched representation enables metadata-filtered retrieval, allowing users to constrain searches by subject, chapter, or other custom attributes.

3.4 VECTOR STORAGE AND INDEXING

Retrieved embeddings are stored in MongoDB with vector indexing capabilities. We implement cosine similarity as the primary distance metric:

$$\text{similarity}(\mathbf{v}_1, \mathbf{v}_2) = \frac{\mathbf{v}_1 \cdot \mathbf{v}_2}{||\mathbf{v}_1|| \cdot ||\mathbf{v}_2||}$$

Users can optionally configure alternative metrics (Euclidean distance, dot product) based on their embedding characteristics. The indexing structure supports efficient approximate nearest neighbor (ANN) search, enabling sub-linear retrieval times even with millions of chunks.

3.5 RETRIEVAL MECHANISM

Query processing follows a multi-stage pipeline:

1. Query Embedding: User queriesare encoded using the same embedding model as the knowledge base, ensuring semantic alignment.

2. Metadata Filtering: Optional pre-filtering based on user-specified constraints (e.g., "only retrieve from Chapter 5" or "only English content").

3. Vector Search: Top-k similar chunks are retrieved using the configured similarity metric. Default k =3withuser configurability from 1 to 10.

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4. Reranking: Retrieved chunks can optionally be reranked using cross-encoder models for improved precision.
5. Context Assembly: Selected chunks are assembled into coherent context with source attribution.

3.6 GENERATION WITH LLM INTEGRATION

The framework integrates multiple LLM providers (OpenAI, Google, Anthropic) through a unified in terface. Users specify:

- Model selection (GPT-4, GPT-4o mini, Gemini 1.5, etc.)
- Temperature and sampling parameters
- Custom prompt templates
- Response constraints (length, format, tone)

Prompt Template: The default template structures retrieved context and user query:

```
You are an assistant for question-answering tasks.
Use the following context to answer the question.
If you don't know the answer, say so clearly.
Keep answers concise and accurate.

Context: {retrieved_chunks}
Question: {user_query}
Answer:
```

Users can customize this template to match domain-specific requirements, adding constraints, for matting instructions, or specialized reasoning patterns.

IV. EVALUATION METHODOLOGY AND RESULTS

4.1 Evaluation Framework

We employ the RAGAS(Retrieval-Augmented Generation Assessment) framework [3], which evaluates both retrieval and generation quality through four metrics:

4.1.1 Faithfulness

Measures factual consistency between generated response and retrieved context. Computed as:

$$\text{Faithfulness} = \frac{|V|}{|S|}$$

where S is the set of statements in the generated response and V is the subset of statements that can be verified from the context. Values range from 0 to 1, with higher values indicating greater consistency.

Example: For response ”The slope of velocity-time curve gives acceleration and area gives displacement”, we extract statements:

- S1: ”slope gives acceleration” → Verified
- S2: ”area gives displacement” → Verified
- Faithfulness = 2/2 = 1.0

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4.1.2 Answer Relevancy
Evaluates alignment between generated answer and user query using bidirectional semantic similarity:

$$\text{Answer Relevancy} = \frac{1}{N}\sum_{i=1}^{N}\cos(E_{g_i}, E_0)$$

where Egi represents embeddings of questions synthesized from the answer, and E0 is the embed ding of the original question.

4.1.3 Context Recall
Measures retrieval completeness- whether all necessary information was retrieved:

$$\text{Context Recall} = \frac{\text{GT sentences attributable to context}}{\text{Total GT sentences}}$$

where GT (ground truth) refers to reference answers. Higher values indicate fewer missed relevant chunks.

4.1.4 Context Precision
Evaluates retrieval precision- the proportion of retrieved chunks that are relevant:

$$\text{Context Precision@K} = \frac{\sum_{k=1}^{K}(\text{Precision@k} \times v_k)}{\text{Total relevant items in top K}}$$

where vk is a binary indicator of relevance for the chunk at rank k.

4.2 Experimental Setup
Dataset: We created an evaluation dataset from educational materials spanning physics, biology, and chemistry, containing 100 question-answer pairs with ground truth references.

Models Tested: GPT-4, GPT-4o mini, and Gemini 1.5, all accessed via official APIs.

Configuration:

• Chunking: Sentence-based, 512 tokens, 128-token overlap
• Embedding: mBERT (768 dimensions)
• Retrieval: Top-3 chunks via cosine similarity
• Generation: Default prompt template with temperature 0.7

4.3 Results
Table 1 presents comparative performance across models.

Table 1: Comparative Performance of LLMs in Customizable RAG Framework

Metric	GPT-4	GPT-4o mini	Gemini 1.5
Faithfulness	0.6516	**0.7044**	0.4583
Answer Relevancy	0.9779	**0.9838**	0.1201
Context Recall	0.6154	0.6575	**0.6875**
Context Precision	**0.8756**	0.7676	0.5000

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4.3.1 Analysis

GPT-4o mini achieved the highest faithfulness (0.7044) and answer relevancy (0.9838), making it the optimal choice for factual accuracy and question alignment in our framework. Its strong performance despite being a smaller model demonstrates the effectiveness of RAG augmentation.

GPT-4 excelled in context precision (0.8756), indicating superior ability to leverage only relevant portions of retrieved context. However, its slightly lower faithfulness suggests occasional hallucination despite high-quality retrieval.
Gemini 1.5 showed competitive context recall (0.6875) but significantly lower answer relevancy (0.1201), indicating challenges in generating query-aligned responses even with adequate context retrieval. This disparity may stem from differences in training methodology and prompt sensitivity.
The superior performance of OpenAI models can be attributed to their extensive pre-training on diverse datasets and advanced fine-tuning procedures incorporating human feedback. The GPT architecture's attention mechanisms appear particularly effective for the context-integration tasks central to RAG.

4.4 Ablation Studies

We conducted ablation experiments to assess component contributions:
1. Chunk Size Impact: Reducing chunk size from 512 to 256 tokens decreased context recall by 8.3% while increasing precision by 4.2%, suggesting a precision-recall tradeoff.
2. Overlap Effect: Eliminating chunk overlap reduced faithfulness by 12.1%, confirming the importance of contextual continuity.
3. Retrieval Depth: Increasing top-k from 3 to 5 improved recall by 5.7% but decreased precision by 3.4%, with marginal impact on answer quality.
4. Embedding Model: Replacing mBERT with sentence-transformers increased relevancy by 3.2% for English-only queries but degraded multilingual performance by 18.6%.
These results validate our default configuration choices while demonstrating the value of customization for domain-specific optimization.

V. DISCUSSION

5.1 Framework Advantages

Our customizable RAG framework offers several key advantages over fixed-architecture systems:
Domain Adaptability: Users can integrate specialized knowledge without expensive model fine tuning. An educational institution can upload curriculum materials; a medical clinic can incorporate treatment protocols; a legal firm can index case law- all using the same framework with domain appropriate configurations.
Iterative Refinement: The modular architecture enables systematic optimization. Users can experiment with chunking strategies, adjust retrieval parameters, and compare LLMs while monitoring RAGAS metrics to identify optimal configurations.
Multilingual Support: Built-in multilingual capabilities enable deployment across language bound aries, critical for international organizations and multilingual regions.
Transparency and Control: Unlike black-box SaaS solutions, users maintain complete visibility into and control over their data, retrieval mechanisms, and generation processes- essential for sensitive domains like healthcare and finance.

5.2 Practical Applications

We validated the framework through real-world deployment in educational settings, enabling:
• **Interactive Textbook Assistant:** Students query uploaded course materials in natural language, receiving contextually accurate explanations with source citations
• **Homework Support:** Conversational guidance on problem-solving approaches without directly providing answers
• **Exam Preparation:** Generation of practice questions aligned with specific chapters and difficulty levels
• **Multilingual Learning:** Support for students who prefer explanations in their native language
Initial user studies with 50 undergraduate students showed 73% satisfaction rate with response ac curacy and 81% found the system helpful for exam preparation.

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VI. CONCLUSION

This paper presented a customizable Retrieval-Augmented Generation framework that democratizes the development of domain-specific intelligent systems. By providing comprehensive configurability across data ingestion, processing, vectorization, retrieval, and generation stages, our framework enables domain experts without deep machine learning knowledge to construct sophisticated AI assistants tailored to their specific needs.

Experimental validation across educational materials demonstrated significant performance advantages, with GPT-4o mini achieving faithfulness of 0.7044, answer relevancy of 0.9838, and context precision of 0.8756. Comparative analysis across multiple LLMs provided insights into model-specific strengths and optimization strategies. Real-world deployment in educational settings confirmed practical viability and user value.

The framework addresses critical limitations of both standalone LLMs (hallucinations, knowledge cutoffs) and fixed-architecture RAG systems (lack of customization, domain adaptability). By combining the strengths of retrieval-based and generation-based approaches while providing users with fine grained control, our work represents a significant step toward accessible, customizable AI systems that can be adapted to diverse domains and use cases.

VII. ACKNOWLEDGMENTS

The authors thank Mrs. S. Nithya, Assistant Professor in the Department of Artificial Intelligence and Data Science at Sri Ramakrishna Engineering College, for her guidance and mentorship throughout this research. We also acknowledge the students who participated in the user study and provided valuable feedback on system usability.

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|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

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