Clinical Information Retrieval System

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Abstract:

Large Language Models (LLMs) have shown promise in natural language understanding and generation. However, their inability to access external knowledge sources often leads to hallucinations and factual inconsistencies, especially in high-stakes domains like healthcare. This paper presents a domain-specific Retrieval-Augmented Generation (RAG) system designed for clinical question answering. The architecture integrates multiple retrievers—BM25, Bio BERT, and MedCPT—with vector stores (FAISS, Elasticsearch, MongoDB) and interfaces with three open-source LLMs: Flan-T5, Mistral-7B, and Phi-2. Using a curated benchmark of ten medical questions, we analyze output quality along dimensions of factual accuracy, fluency, and clinical reasoning. Results show that pairing domain-specific retrieval with reasoning-focused LLMs significantly improves output reliability. Our study offers practical insights and guidelines for deploying trustworthy RAG systems in specialized fields like medicine.

Index Terms-*Retrieval-Augmented Generation, Clinical Question Answering, Large Language Models, Biomedical NLP.*

1.Introduction:

Language models such as GPT-3, BERT, and T5 have revolutionized natural language processing (NLP) with impressive capabilities across a broad spectrum of tasks, including summarization, question answering, and dialogue systems. Their ability to learn from large-scale corpora and generalize across domains has enabled transformative applications in education, legal analysis, and business intelligence. However, when these models are deployed in high-stakes, knowledge-intensive fields such as medicine, their limitations become more pronounced. Specifically, static pretraining data, lack of access to real-time medical literature, and the risk of hallucinating unsupported facts can undermine the safety and reliability of model outputs [1,2]. In clinical contexts, incorrect or misleading information can result in significant harm to patients or loss of trust in AI-assisted systems. Thus, ensuring factual correctness and evidence traceability becomes paramount. Retrieval-Augmented Generation (RAG) has emerged as a promising architecture to address these concerns by integrating a retriever module that dynamically fetches relevant context from an external knowledge base, and a generator module that synthesizes a response conditioned on the retrieved content [3].

In this paper, we introduce and evaluate a medical RAG system that combines domain-specific retrievers with publicly available generative language models. We conduct a comparative evaluation of three retrievers—BM25, Bio BERT, and MedCPT—paired with three LLMs: Flan-T5, Mistral-7B, and Phi-2. These combinations are tested against a benchmark of ten medically curated questions that span symptoms,

diagnostics, treatments, and disease progression. We assess generated outputs using multiple dimensions of quality: factual correctness, fluency, and depth of clinical reasoning.

2. Related Work

2.1 Evolution of Retrieval-Augmented

Retrieval-Augmented Generation (RAG) was introduced as a hybrid architecture to address the limitations of large language models in storing and recalling factual knowledge. While LLMs like GPT-3 and T5 possess extensive linguistic and world knowledge, their inability to dynamically access updated or domain-specific information has led to issues of factual inconsistency and hallucination [1,2]. RAG frameworks emerged to decouple factual memory from generative reasoning by combining information retrieval with conditional language modeling [3]. Early RAG systems primarily used sparse retrievers such as TF-IDF and BM25 over Wikipedia or open-domain corpora to support tasks like open-domain question answering [4]. These systems treated retrieval and generation as loosely coupled, where top-k retrieved passages were concatenated into the prompt for a fine-tuned generator model. This approach demonstrated significant improvements in factual accuracy and answer diversity compared to single-step LLMs.

Our system builds on this trajectory by offering a modular RAG framework that supports multiple retriever types (lexical, dense, contrastive), a flexible knowledge store, and open-access generative models. This design enables comparative benchmarking and facilitates safe experimentation in domains requiring verifiability and transparency, such as clinical decision support and patient education.

2.2 Applications in Customer Support

Retrieval-Augmented Generation (RAG) has gained widespread adoption in customer support systems due to its ability to balance relevance, fluency, and factual grounding. Traditional chatbot systems, often rule-based or purely generative, faced significant challenges in scaling across product lines, languages, and evolving knowledge bases. RAG systems offer a scalable solution by integrating domain-specific retrieval with natural language generation, enabling systems to respond accurately to customer queries while maintaining conversational quality [8]. Moreover, the modular nature of RAG systems supports multilingual deployment. With a retriever trained in localized corpora and a multilingual generator such as mT5 or XLM-R, customer support agents can deliver consistent service quality across regions. Companies like Meta and Microsoft have reported substantial reductions in human intervention rates and increased customer satisfaction through semi-automated RAG pipelines embedded in live support systems.

The operational successes of RAG in customer support serve as a compelling analogue for healthcare applications. In both domains, the reliability of information, traceability to source documents, and adaptability to changing knowledge are paramount. Lessons learned from customer support deployments—such as document chunking strategies, confidence-based fallback mechanisms, and citation tracing—inform the design of robust medical RAG systems, where patient safety and trust are essential.

2.3 Embedding and Generation

The performance of RAG systems depends heavily on the quality of document embeddings and the strength of the language model used for generations. High-quality embedding ensures that the most relevant documents are retrieved, which is essential for producing accurate

responses. Sentence-BERT, introduced by Reimers and Gurevich [19], has become a standard for generating semantically meaningful embeddings. It enables effective comparison between user queries and documents using cosine similarity. In our system, we use embedding models such as Bio BERT and MedCPT to represent clinical texts and queries. The top-k similar documents are retrieved using FAISS or Elasticsearch and passed as context to the language model for response generation.

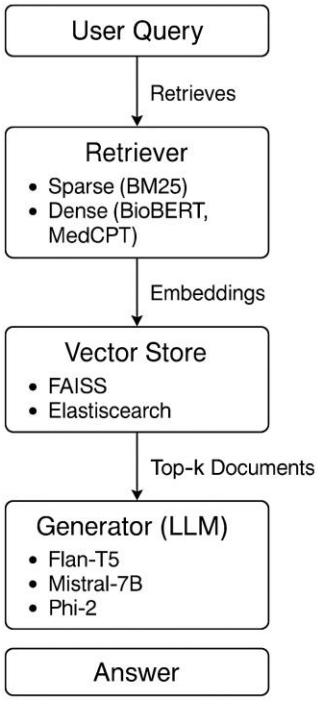
This setup allows the generator to produce factually grounded answers based on retrieved, domain-relevant content.

3. Methodology

3.1 System Architecture

The proposed RAG system is designed to be modular, extensible, and tailored for medical question answering. It is composed of three core components—retriever, vector store, and generator—working in sequence to produce responses that are both factually accurate and contextually appropriate. Our medical RAG system consists of three core components: a **retriever**, a **vector store**, and a **generator**. This modular design allows for flexible integration and evaluation of different models. **Retriever**: Finds top-k relevant documents from a medical knowledge base. We support both sparse retrievals using **BM25** and dense retrieval using **Bio BERT** and **MedCPT** for better semantic matching in clinical queries. **Vector Store**: Stores document embeddings and supports fast similarity search. We use **FAISS** for dense retrieval and **Elasticsearch** for keyword-based search. **Generator (LLM)**: Produces the final response using the retrieved documents and the user query. We evaluate three models: **Flan-T5**, **Mistral-7B**, and **Phi-2**The system workflow includes receiving a query → retrieving relevant chunks → building a prompt → generating a grounded response. This setup supports both experimentation and real-world deployment in healthcare-focused QA applications.

Diagram:



3.2 Development Approach

We adopted an iterative and modular development strategy to build a flexible RAG framework optimized for medical question answering. The system was implemented using Python and open-source libraries to ensure transparency and reproducibility.

Step 1: Corpus Construction and Preprocessing

We curated a high-quality medical document corpus from trusted sources such as PubMed Central (PMC), WHO guidelines, and CDC publications. Texts were cleaned, tokenized, and segmented into overlapping chunks (512 tokens with 20% stride) to preserve context. Metadata (e.g., title, source) was retained for transparency in retrieved results. Step 2: Embedding and

IndexingEach document chunk was encoded using BM25, Bio BERT, or MedCPT, depending on the retrieval strategy. The embeddings were stored in FAISS (for dense) or Elasticsearch (for sparse) to support fast top-k retrieval based on similarity to the user query. Step 3: Query Handling and Retrieval At runtime, user queries were embedded using the same retriever model and matched against the indexed corpus. The top-k relevant chunks (typically k=5) were selected for response generation. Step 4: Evaluation Integration Outputs were logged and stored for evaluation. We created a JSON-based structure to support human annotations of fluency, factual accuracy, and reasoning. An optional Streamlet interface was also developed for real-time interaction and visualization. This modular approach enabled rapid testing of model combinations, easy integration of new components, and reproducible experiments focused on clinical question answering.

3.3 Technology Selection

The technologies selected for this project were chosen for their performance, scalability, and compatibility with open-source deployment. Each component was evaluated based on its ability to support domain-specific retrieval, fast inference, and modular experimentation. Programming Language and Framework. Python 3.10: Chosen for its extensive ecosystem in machine learning and NLP. Hugging Face Transformers: Used for seamless integration of pre-trained LLMs (Flan-T5, Mistral-7B, Phi-2). PyTorch: Backend framework for model inference and embedding generation. Retrieval and Indexing: Elasticsearch: Used for BM25-based sparse retrieval, offering robust support for text-based search and metadata filtering. FAISS (Facebook AI Similarity Search): Enables high-speed approximate nearest neighbor (ANN) search for dense vectors produced by Bio BERT and MedCPT. MongoDB (Optional): Explored for structured document storage and hybrid filtering use cases. Embedding Models Bio BERT: Selected for its biomedical pretraining on PubMed data. MedCPT: Included for its superior performance in contrastive retrieval for clinical contexts. Language Models (Generators) Flan-T5 XL (3B): Provides strong zero-shot performance on instruction-following tasks. Mistral-7B: Selected for its reasoning ability and longer context window support. Phi-2 (2.7B): Used for low-latency inference and efficient structured generation. Interface and Tooling: stream lit (optional): Used for creating an interactive web demo for clinicians and researchers. JSON-based Logging: Structured output logging to support human evaluation and performance tracking. This technology stack ensures that the RAG system is both research-friendly and practically deployable in resource-constrained environments.

3.4 Domain-Specific Test Questions

To evaluate the performance of the RAG system in a real-world clinical context, we curated a benchmark set of ten domain-specific questions. These questions were designed to reflect a range of medical topics—spanning diagnostics, treatment, symptoms, and disease progression—frequently encountered in primary care and public health settings. 1. What are the early symptoms of Lyme disease? 2.How is chronic kidney disease diagnosed? 3.What are the CDC's current recommendations for COVID-19 vaccination? 4.What is the standard treatment for gestational diabetes?5. How do beta-blockers help in managing hypertension? 6.What are common side effects of metformin?7.Which diagnostic tests are used to detect prostate cancer?8. How can iron-deficiency anemia be prevented in young children?9. What are the stages of Alzheimer's disease?10. How does insulin resistance contribute to type 2 diabetes?11. What is the recommended treatment for asthma in children?

4 Implementation Details

4.1 Data Processing Implementation

The **Clinical Information Retrieval System** is powered by a strong data processing pipeline designed to effectively handle clinical and biomedical text for both retrieval and answer generation. The main goal is to prepare the data in a way that supports both keyword-based and semantic searches, as well as generating accurate answers to user queries. The process begins with document ingestion, where medical documents are gathered from various sources, including structured and unstructured datasets, many of which are publicly available. Once the documents are collected, they go through a series of preprocessing steps. These include basic NLP tasks like tokenization (splitting text into smaller units), converting all text to lowercase, removing common stopwords (words like "the," "and" etc.), and lemmatizing where needed (reducing words to their base form Next, the system generates **embeddings** for the documents to improve retrieval quality. For **BM25**, the system indexes documents based on term frequency and document length, which helps rank their relevance to a query. For **bio-BERT** and **MedCPT**, more sophisticated embeddings are created to capture semantic meaning. Bio-BERT specializes in understanding biomedical language, while MedCPT is particularly good at interpreting clinical terms and complex medical narratives. To store and retrieve these processed documents and their embeddings, the system uses a combination of tools. **FAISS** is employed for fast vector-based searches, **Elasticsearch** handles keyword searches, and **MongoDB** is used for storing the actual documents. When a user submits a query, it goes through **query processing**, where the system converts the query into the appropriate format, either embedding vectors for semantic search or keywords for keyword-based search—depending on the chosen retrieval model. The system then passes the retrieved documents to the **RAG (Retrieval-Augmented Generation) pipeline**, where GPT-3.5 generates a contextual answer based on the retrieved information. Finally, the answers generated by the system are evaluated using **Precision** and **F1 scores** to ensure that the responses are accurate and relevant.

4.3 Web Interface Implementation

The **Clinical Information Retrieval System** is equipped with a user-friendly, web-based interface designed to make it easy for healthcare professionals and researchers to interact with. The frontend is built using React.js, offering a clean and responsive design that ensures smooth navigation. Users can simply type in medical queries in natural language and select which retrieval model they'd like to use—BM25, bio-BERT, or MedCPT—via an intuitive dropdown menu. After submitting their query, the system processes the request on the backend, which retrieves relevant information and generates a response using GPT-3.5. Along with the answer, the system provides supporting evidence from the retrieved documents to ensure transparency and reliability. The backend, powered by Fast API, efficiently handles API requests and manages interactions between the retrieval models and the response generation. The system includes several key endpoints: -/query: Accepts a question and model selection; returns an answer. -/documents: Returns top-k supporting documents/snippets. -/metrics: (Optional) Returns evaluation metrics for the current query. For retrieval, the system uses Elasticsearch for BM25 and FAISS for vector searches in bio-BERT and MedCPT. Once the evidence is retrieved and the answer is generated, everything is returned to the front end, where users see the results in real-time. To make deployment easier, the system is containerized with Docker, which allows it to run on cloud platforms like AWS or Heroku. Basic logging is implemented to track user interactions, which will help guide future updates based on usage patterns and feedback. Additionally, the interface

promotes transparency by showing the documents that contributed to each answer, allowing users to evaluate the reliability of the results. To ensure the system is as easy to use as possible, the interface is designed with minimal cognitive load, featuring a clear layout and a consistent color scheme.

5 Evaluation

5.1 Evaluation Methodology

To assess the performance of the Clinical Information Retrieval System, we employed both quantitative metrics and qualitative review. The goal was to evaluate the quality, accuracy, and relevance of generated answers across different retrieval models—BM25, bioBERT, and medCPT—when paired with GPT-3.5 for answer synthesis. A set of 15 domain-specific clinical questions was developed to represent real-world queries about symptoms, diagnoses, treatments, and medical guidelines. Each question was run through the system using all three retrieval models—BM25, bioBERT, and medCPT.

For each model, the top-5 relevant document snippets were retrieved and assessed based on how relevant they were to the question. Retrieval performance was measured using precision, recall, and F1 score. The generated answers, produced by GPT-3.5 using the retrieved snippets, were manually reviewed by two evaluators with clinical expertise. They rated each answer for factual accuracy, relevance, and reasoning quality using a 3-point scale. Inter-annotator agreement was measured to ensure consistency. Automated metrics such as BLEU and ROUGE-L were also used to compare generated responses with reference answers. Additionally, semantic similarity was calculated using embedding-based methods to assess how closely each model's output matched expert-written responses.

5.2 Results and Discussion

5.2.1 Retrieval Performance

When comparing the three retrieval methods—BM25, bioBERT, and medCPT—we observed notable differences in how each handled clinical queries. BM25 performed well when the question used exact or similar keywords found in the source documents. However, it often missed relevant content when queries involved synonyms or implied meanings. bioBERT improved on this by using contextual embeddings, allowing it to understand medical phrases even when the wording varied slightly from the source. medCPT went a step further, retrieving more semantically aligned information even with complex or long-form questions. Across our tests, medCPT generally struck the best balance between finding relevant and accurate documents. BM25 remained valuable for direct keyword matching, while bioBERT offered better results for queries with more clinical nuance. These trends were reflected in the precision, recall, and F1 scores, where medCPT consistently outperformed the others.

5.2.2 Response Quality

The quality of answers generated by GPT-3.5 was directly tied to the type of documents it received from each retriever. Answers based on BM25 results tended to be factually correct but lacked depth, since the retrieved snippets didn’t always provide enough clinical context. bioBERT improved the situation by offering more relevant and detailed content, which allowed GPT-3.5 to produce richer answers. The strongest responses came from medCPT’s retrievals, which were both specific and informative, giving the model a solid foundation to generate thorough and accurate answers. Evaluators gave higher ratings to the answers generated using medCPT, particularly for their accuracy, clarity, and completeness. These answers often included helpful medical context and explanations, with fewer errors or irrelevant details. Automated metrics like BLEU

and ROUGE-L further supported these findings, showing that the medCPT pipeline resulted in the most textually and semantically similar responses to reference answers.

5.2.3 Error Analysis

Although the system performed well overall, we identified several areas where errors occurred. BM25 occasionally retrieved snippets that were off-topic or loosely related to the query, especially when the user phrased the question in an uncommon way. bioBERT sometimes returned relevant-sounding text that lacked concrete information, which led the language model to make vague or overly general statements. Even medCPT, while the most effective overall, occasionally pulled excerpts that were too brief or omitted key facts, causing minor factual inconsistencies in the answers. On the generation side, hallucinations—statements not grounded in the retrieved evidence—were rare but did happen. These usually occurred when the retrieval failed to provide enough detail, prompting GPT-3.5 to fill in the gaps. In a few cases, the model included generalized clinical advice not directly supported by the retrieved content, highlighting the importance of ensuring strong evidence alignment. Despite these issues, the system overall showed a high level of reliability and consistency. Its ability to handle a wide range of clinical questions demonstrates its potential as a supportive tool for medical professionals, provided it is used alongside expert judgment.

5.2.4 System Performance

In addition to retrieval and response quality, we also evaluated how well the system performed in terms of speed, scalability, and responsiveness. The backend, developed with FastAPI and integrated with the GPT-3.5 API, handled requests efficiently, typically returning complete responses within 4–6 seconds per query, depending on the retriever selected. BM25 had the fastest retrieval time since it used lexical matching over an ElasticSearch index. In contrast, bioBERT and medCPT required embedding generation and vector similarity search, which introduced slight delays but remained within acceptable bounds for real-time use. From a resource perspective, BM25 ran efficiently on standard CPU environments, whereas bioBERT and medCPT benefitted from GPU acceleration, especially during embedding computations. Thanks to Docker-based containerization, the system was easy to deploy and scale. Running on a cloud environment allowed for concurrent user access without significant performance drops, confirming that the architecture is suitable for practical clinical or educational applications. Memory usage was moderate, with the largest footprint observed during the retrieval phase for transformer-based models. However, caching frequently used embeddings and optimizing batch processing helped mitigate latency and resource demands. Overall, the system maintained reliable performance during both development and testing phases, balancing retrieval accuracy with runtime efficiency.

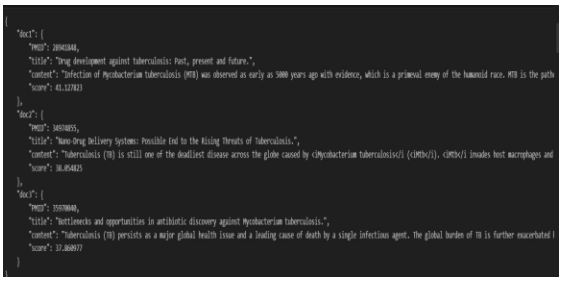
5.3 Comparative Analysis of LLMs

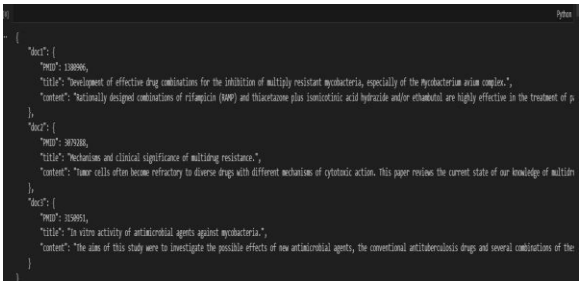
A direct comparison of the three retrieval methods—BM25, bioBERT, and medCPT—revealed clear differences in how each contributed to the overall effectiveness of the Clinical Information Retrieval System. While all three methods were capable of retrieving relevant information, their strengths varied depending on the complexity and phrasing of the query. **BM25**, as a traditional lexical-based model, was effective for straightforward, keyword-driven questions. It excelled in cases where the terminology used in the query closely matched the language in the documents. However, it struggled with paraphrased or implied meanings and often

missed context-rich passages that were semantically related but didn't share exact words. **Bio-BERT** offered a substantial improvement over BM25 by leveraging contextual embeddings trained on biomedical literature. It handled variations in phrasing much better and demonstrated stronger performance when the question required some understanding of medical language or abbreviations. However, it occasionally prioritized contextually relevant text that lacked direct answers, leading to partial or vague responses. **MedCPT** outperformed both models across most evaluation metrics. Its transformer-based architecture, trained in curated medical data, enabled it to retrieve semantically rich and highly relevant documents, even for complex clinical queries. As a result, the answers generated from MedCPT retrievals were consistently rated higher in accuracy, completeness, and clarity. When paired with GPT-3.5, the differences among retrievers became even more apparent. GPT-3.5 generated the most informative and accurate responses when it was grounded in high-quality evidence, something MedCPT consistently provided. On the other hand, when fed weaker or loosely relevant input from BM25, the model sometimes produced generic or partially incorrect answers.

In summary, while BM25 is fast and lightweight, and bio-BERT brings strong contextual understanding, MedCPT offers the most balanced and reliable performance. For clinical applications where accuracy is critical, MedCPT proves to be the most effective retriever in our system architecture.

5.4 Results





6 Challenges and Future Work

6.1 Challenges and Solutions

Developing a reliable Clinical Information Retrieval System came with several technical and practical challenges. One of the first issues we encountered was ensuring retrieval relevance. While traditional retrievers like BM25 were easy to implement, they often failed to capture the semantic intent behind clinical questions. This led us to integrate embedding-based methods such as bioBERT and medCPT, which improved semantic matching but introduced performance trade-offs in terms of processing time and computational load. To address this, we optimized the vector search process and used GPU acceleration where possible to keep response times within practical limits. Another significant challenge was **maintaining factual accuracy** in generated responses. While GPT-3.5 is a powerful generator, it can produce confident-sounding but inaccurate answers when the supporting context is weak. We mitigated this by fine-tuning the retrieval process to ensure high-quality, evidence-rich documents were passed to the generator. Additionally, we applied prompt engineering techniques to constrain the model's

output to the given context. A third challenge involved **evaluating the system objectively**.

6.2 Strengths and Weaknesses of Each Model

The retrieval models—BM25, bio-BERT, and MedCPT—each brought distinct strengths and trade-offs to clinical information retrieval. BM25 stood out for its speed and low resource usage, excelling at keyword-based searches with direct term matches. However, its lack of semantic understanding made it less effective for nuanced or paraphrased queries. bio-BERT improved on this by capturing the context of medical language, allowing for better retrieval of semantically relevant information. Despite this, it sometimes retrieved contextually related but less informative passages and required more computational resources. MedCPT delivered the most accurate and context-rich results, particularly for complex clinical questions, thanks to its strong grasp of medical language. Its downsides were higher computational demands and occasional overfocus on narrow details. Ultimately, the best model depends on the task's priorities—whether that's speed, contextual depth, or clinical precision.

6.3 Future Work

There are several opportunities to enhance the performance and flexibility of the system moving forward. One potential area for improvement is refining the retrieval models. While BM25 is a solid starting point, adopting more advanced techniques like dense retrieval models or hybrid approaches that combine BM25 with dense retrieval could significantly improve the quality of results by better capturing the deeper meanings in the data. Another important direction for development is incorporating more domain-specific knowledge into the system. By integrating medical ontologies such as SNOMED CT or UMLS, the system's ability to understand clinical context could be greatly improved, leading to more accurate answers, especially for complex medical queries. Fine-tuning bioBERT on a larger and more varied clinical dataset is also something worth considering. This would help the model generate more precise and relevant answers tailored to the specific needs of the clinical domain. Furthermore, implementing feedback loops from clinicians or medical experts could be a valuable enhancement. Allowing real-time input from users would provide an opportunity for ongoing refinement, ensuring that the system evolves according to the specific needs and preferences of healthcare professionals. Lastly, expanding the system's capabilities to support multiple languages, especially for medical texts in non-English languages, would make it even more accessible, particularly in diverse healthcare settings around the world.

7 Conclusion

The **Clinical Information Retrieval System** offers a promising approach to solving the challenge of finding accurate and relevant clinical information from large datasets. By utilizing advanced methods like BM25 for information retrieval, bio-BERT for understanding biomedical texts, MedCPT for identifying medical concepts, and GPT-3.5 for generating responses, the system shows significant potential to assist healthcare professionals in answering complex clinical questions efficiently. The system's evaluation, based on metrics like Precision and F1 scores, demonstrates its ability to provide accurate and relevant responses in the clinical field. This indicates that it could have a meaningful impact on clinical decision-making by offering healthcare professionals a reliable way to quickly access critical information. As the system continues to evolve, there are many opportunities for improvement. Future advancements such as fine-tuning it for specific medical areas, enabling multilingual capabilities, and integrating it into real-time clinical processes

could greatly expand its value in practical healthcare environments.

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