Leveraging Knowledge Graph-Enhanced LLMs for Context-Aware Medical Consultation

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Abstract

Recent advancements in large language models have significantly influenced the field of online medical consultations. However, critical challenges remain, such as the generation of hallucinated information and the integration of up-to-date medical knowledge. To address these issues, we propose **I**nformatics **Llama** (ILlama), a novel framework that combines retrieval-augmented generation with a structured medical knowledge graph. ILlama incorporates relevant medical knowledge by transforming subgraphs from a structured medical knowledge graph into text for retrieval-augmented generation. By generating subgraphs from the medical knowledge graph in advance, specifically focusing on diseases and symptoms, ILlama is able to enhance the accuracy and relevance of its medical reasoning. This framework enables effective incorporation of causal relationships between symptoms and diseases. Also, it delivers context-aware consultations aligned with user queries. Experimental results on the two medical consultation datasets demonstrate that ILlama outperforms the strong baselines, achieving a semantic similarity F1-score of 0.884 when compared with ground truth consultation answers. Furthermore, qualitative analysis of ILlama's responses reveals significant improvements in hallucination reduction and clinical usefulness. These results suggest that ILlama has strong potential as a reliable tool for real-world medical consultation environments.[1]

1 Introduction

Traditional online medical consultation platforms, such as HealthCareMagic[2] and iCliniq[3], rely on medical professionals to answer patient queries and provide expert advice. However, due to their dependence on human labor, these systems face limitations in delivering real-time responses, as experts require significant time to review inquiries and generate appropriate answers (Cao et al., 2022). To address this issue, rule-based medical consultation systems have been introduced (Amato et al., 2017; Mishra et al., 2023; Rosruen and Samanchuen, 2018; Huang et al., 2018). Nevertheless, these systems often struggle to handle complex symptoms and patient-specific queries, as they rely on predefined rules that lack flexibility and adaptability.

Recently, large language model (LLM)-based consultation systems, such as ChatDoctor (Li et al., 2023), have emerged as promising alternatives. These systems typically extract keywords from user queries to retrieve relevant medical information from sources like Wikipedia or custom disease databases. However, their reliance on potentially inaccurate keyword extraction may lead to search failures and hallucinations, failing to capture essential disease-symptom relationships. While dense embedding-based retrieval methods (Karpukhin et al., 2020) can alleviate keyword extraction errors, they still have limitations in capturing the complex symptom-disease relationships essential for medical consultations. For example, distinguishing whether shortness of breath and fatigue arise from a serious condition like lung cancer or a more benign cause such as anemia requires an understanding of such causal relationships.

To overcome these limitations, we propose a novel framework for real-time medical consultation, called **I**nformatics **Llama** (ILlama), which improves the response quality as measured by embedding-based evaluation metrics by incorporating structured medical knowledge. To ensure that ILlama performs reliably not only on known data distributions but also in unfamiliar real-world scenarios, we adopt both in-distribution and out-of-distribution evaluation protocols throughout this work. This setup allows us to assess the model's generalizability across different sources of med-

[1] The code will be released upon publication.

[2] https://www.askadoctor24x7.com

[3] https://www.icliniq.com

ical consultations. ILlama leverages retrieval-augmented generation (RAG) (Lewis et al., 2020b) by incorporating medical knowledge from a structured knowledge graph (KG) built upon the unified medical language system (UMLS)[4]. UMLS is updated regularly, which aligns well with common retraining cycles. Therefore, instead of frequently retraining the language model, it is more efficient to update the KG, enabling practical and timely integration of new medical information.

Unlike keyword-dependent approaches, ILlama improves both retrieval efficiency and reliability. Keyword-extraction methods often misinterpret the intent of user queries and, in many cases, fail to return relevant results if relevant medical information for the extracted keywords is unavailable. By employing a KG-based retrieval approach (Luo et al., 2025), ILlama effectively represents disease-symptom causal relationships, enhancing the contextual relevance and accuracy of diagnostic responses.

In addition, ILlama tackles two core limitations prevalent in existing dense embedding-based augmentation systems: (1) the incompleteness of external knowledge representations and (2) the difficulty in aligning user queries with the embedded knowledge space (Varshney et al., 2023). ILlama addresses the incompleteness of the KG by constructing subgraphs that enrich sparse regions with semantically related triples. It is also designed to alleviate the challenge of aligning user queries with the KG structure by embedding each triple and integrating it into the answer generation process. This approach enables more accurate semantic matching and enhances the clinical relevance of the generated responses. Specifically, embedding triples allows the model to retrieve more precise symptom-disease associations, reducing factual errors, while the structured knowledge context provided by the KG improves the alignment of responses with real-world clinical reasoning.

We validate the effectiveness of ILlama using two medical consultation datasets with different characteristics. Specifically, we conducted experiments with publicly available data collected from HealthCareMagic and iCliniq. For in-distribution evaluation, we use the HealthCareMagic dataset, which includes separate training, validation, and test splits. For out-of-distribution evaluation, we use real-world consultation records from the iCliniq platform, serving as the test set. ILlama$_{7B}$, which is based on the same base model as ChatDoctor, achieves F1 scores of 0.866 and 0.851 on the in-distribution and out-of-distribution datasets, respectively, and outperforms all baseline models. These scores are computed based on the semantic similarity between the generated responses and the ground truth consultation records. ILlama$_{8B}$, with a more powerful backbone LLM, further improves these results, achieving scores of 0.884 and 0.871, respectively. The reliability of the generated responses is further supported by a qualitative evaluation that assesses their clinical quality.

In summary, our contributions are three-fold:

- We propose ILlama, a framework that reduces hallucinations by integrating structured medical knowledge and explicit disease-symptom causal relationships into LLMs. This framework facilitates easy knowledge updates by allowing replacement of the underlying UMLS-based KG.
- ILlama utilizes subgraphs from a UMLS-based KG, which are transformed into document form, combined with vector search techniques, enabling precise retrieval and integration of medically relevant knowledge into the answer generation process.
- Our framework achieves state-of-the-art performance across multiple datasets, with the best results observed on the HealthcareMagic dataset, significantly improving the reliability and usefulness of automated medical consultation systems.

2 Related Works

2.1 Early Medical Consultation Systems

Early systems (Amato et al., 2017; Mishra et al., 2023; Rosruen and Samanchuen, 2018; Huang et al., 2018) used rule-based approaches for simple Q&A interactions, easing the burden on healthcare professionals but failing to handle complex symptoms and disease interactions. To overcome this, medical-specialized models using natural language processing technologies (Lee et al., 2020; Yuan et al., 2022; Lu et al., 2022) were developed, yet challenges in incorporating structured medical knowledge and understanding causal relationships between symptoms and diseases remain. LLMs

[4] https://www.nlm.nih.gov/research/umls/archive/archive_home.html

such as GPT-4 (Achiam et al., 2023) have catalyzed the development of models capable of sophisticated medical consultations (Thirunavukarasu et al., 2023; Li et al., 2024; Toma et al., 2023; Chen et al., 2023; Luo et al., 2022; Yang et al., 2024), although persistent challenges remain, including hallucinations and the incorporation of up-to-date medical information (Vaishya et al., 2023; Hadi et al., 2024). To mitigate these issues, we incorporate a UMLS-based KG that enables accurate identification of disease relationships and contextual information retrieval, thereby supporting more clinically relevant and context-aware consultations.

2.2 Knowledge-Based LLMs in Medical Consulting

To address the limitations of LLMs, such as hallucinations, lack of timely medical knowledge, and insufficient adaptability to patient-specific contexts, recent research has explored the integration of real-world knowledge to enhance performance in medical applications. Among these approaches, the combination of LLMs with KGs has demonstrated effectiveness in incorporating external information. For example, KG-enhanced models have been used for diagnosis prediction (Gao et al., 2025), graph-augmented medical dialogues (Varshney et al., 2023), and factual medical question answering (Guo et al., 2022; Martino et al., 2023). However, many of these methods rely on incomplete KGs, which are often limited in coverage or biased toward certain clinical entities. They also struggle with aligning unstructured user queries to structured graph elements, both of which hinder their clinical precision. In contrast, ILlama introduces subgraph-based retrieval and semantic reranking to improve knowledge relevance and integration, offering more accurate and context-sensitive medical consultations.

3 Method

The proposed framework consists of three main components: Retriever, Reranker, and Generator. Medical knowledge from the KG is first segmented into subgraphs and transformed into documents in natural language form, which serve as input across all stages. Section 3.1 describes how the Retriever identifies subgraphs semantically relevant to the input query. Section 3.2 presents the Reranker, which employs a cross-encoder (Reimers and Gurevych, 2019) to rerank the retrieved documents in natural language form. Section 3.3 explains how the Generator uses the top-ranked documents to generate the final response. The overall process is illustrated in Figure 1.

3.1 Retriever: Enhancing Medical Knowledge

In medical consultations, it is essential to provide accurate, context-aware information without hallucinations. Our framework requires comprehensive medical knowledge, particularly regarding causal relationships between symptoms and diseases. To achieve this, we incorporate a KG based on UMLS, which enables the language model to effectively capture these relationships and allows targeted retrieval of relevant medical facts from the KG. This ensures that responses are both precise and contextually appropriate to the user's query.

3.1.1 Triple-Centric Knowledge Structuring for Medical Reasoning

To effectively represent medical knowledge within the model, we adopt the Triple2Seq (Bi et al., 2024) method to segment the UMLS-based KG into meaningful and contextually coherent subgraphs. A segmented KG (i.e., subgraph) is a structured representation where nodes denote medical concepts (e.g., diseases, symptoms, and treatments) and edges define the relationships among them (e.g., "has symptom", "treated by", and "has causes").

Each subgraph $\mathcal{T}_g$ is composed of a center triple $\mathcal{T}_c$ (e.g., Lung Cancer-has symptom-Fatigue), representing a core medical concept, and a set of neighboring context triples $\mathcal{T}_N$ (e.g., Lung Cancer-has causes-Smoking) that provide additional medical facts related to the center triple:

$$\mathcal{T}_g = \mathcal{T}_c \cup \mathcal{T}_N. \tag{1}$$

$\mathcal{T}_N$ includes all triples connected to the center triple via its neighboring nodes in the KG and is defined as:

$$\mathcal{T}_N = \{\mathcal{T}_i \mid \mathcal{T}_i \in \mathcal{N}\}, \tag{2}$$

where $\mathcal{N}$ denotes the set of nodes that are directly linked to the center concept in the graph. For example, if the center triple corresponds to a disease such as lung cancer, the context triples may include related symptoms (e.g., shortness of breath and fatigue), diagnostic procedures (e.g., chest X-ray), or causes (e.g., smoking or air pollution). By organizing knowledge in this localized and relation-centric

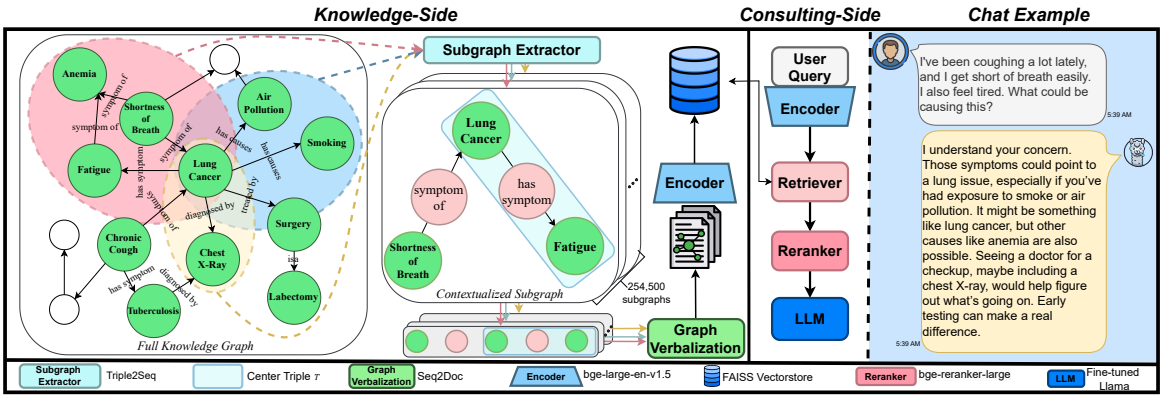

Figure 1: Overall architecture for medical query answering using contextualized subgraphs from the UMLS-based KG. These subgraphs are encoded and stored in a vector database, then combined with the user query to generate the final response using the Llama model.

manner, the model is guided to focus on medically relevant and causally connected concepts, thereby enhancing the contextual consistency of the generated responses. Furthermore, this structure enables more accurate and context-aware diagnosis and consultation based on the patient's reported symptoms, ultimately improving the reliability and practicality of medical dialogue systems.

3.1.2 Subgraph-to-Text Transformation

The UMLS-based KG represents relationships between medical concepts using a subject–predicate–object triple structure, which closely resembles the structure of natural language sentences. Leveraging this property, we convert each triple into a natural sentence. This transformation reconstructs the structural relationships in the graph into a coherent narrative, allowing the model to intuitively understand the meaning and connections between medical entities. As a result, the graph-based knowledge is naturally integrated into the text generation process, enabling the model to learn richer contextual information.

We further define subgraphs consisting of a center triple and its related neighboring triples. All triples within each subgraph are converted into natural sentences and aggregated into a single document, forming a semantically coherent and logically structured unit of knowledge. A detailed example of this subgraph-to-document transformation, including the rule-based sentence structure and the resulting document format, is provided in Appendix B.

3.1.3 Pseudo Query Generation for Fine-Tuning Medical Search System

In our framework, document-form subgraph encoder and reranker models pre-trained on general domain data are not sufficient to accurately retrieve medical information grounded in a UMLS-based KG. To improve their ability to understand and retrieve UMLS-specific representations, these models should be fine-tuned on domain-specific data. However, manually constructing high-quality query-document pairs is impractical and costly. To address this, we propose an automated pipeline based on frozen Llama3.1_{8B} (Dubey et al., 2024) models that generates and filters training data without human supervision. The pipeline consists of two core components: a pseudo query generator, which produces queries reflecting key contents of each document, and an evaluator, which filters these queries based on two criteria, patient centeredness ([`Patient`/`notPatient`]) and document relevance ([`Relevant`/`Irrelevant`]).

As illustrated in Figure 2, the system generates multiple candidate queries per document, evaluates them, and filters those that meet the training standards. Although the evaluator operates in a zero-shot setting without parameter updates, it consistently selects high-quality query-document pairs and generalizes well across unseen pairs. These filtered pairs are subsequently used to fine-tune the document-form subgraph encoder and reranker models, contributing to improved retrieval accuracy and consistency. Details on the objective functions used for each model are provided in Appendix C. Furthermore, while our pipeline focuses on medical consultation documents in this study, it can be

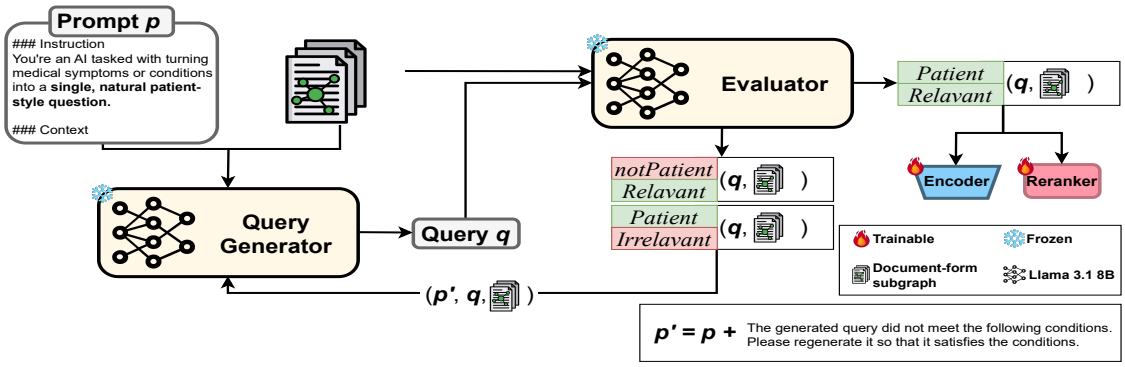

Figure 2: Overview of training data generation process for the document-form subgraph encoder and reranker. A fixed query generator creates questions that a patient is likely to ask, and an evaluator checks if they match a patient-like style and are relevant to the document. If they don't meet the criteria, they are regenerated. The final data trains *bge-large-en v1.5* and *bge-reranker-large*, enhancing the model's ability to understand and process patient-oriented queries.

easily adapted to other domains by adjusting the evaluation criteria.

3.1.4 Document Embedding and Vector Retrieval

We fine-tuned the *bge-large-en-v1.5* (Xiao et al., 2024) model to generate embeddings for documents derived from the subgraph, optimizing its ability to capture semantic nuances. These embeddings are stored in a vector database using FAISS (Johnson et al., 2019), which is optimized for large-scale similarity searches. By integrating maximum inner product search (Shrivastava and Li, 2014), we efficiently retrieve relevant documents, ensuring low-latency and high-precision results, crucial for real-time applications like conversational agents.

3.2 Reranker: Filtering for Exact Knowledge

To enhance the accuracy of retrieved documents, we implemented a reranking process using the fine-tuned *bge-reranker-large*[5] model. The cross-encoder simultaneously encodes both the user's query and the documents, effectively capturing complex interactions and evaluating the relevance and specificity of each document in relation to the user's needs. Based on the reranking scores, documents are reordered to prioritize those most relevant to the query and tailored to the user's context. This ensures the model can reflect more precise and relevant information in the final response, ultimately providing answers that are accurate and aligned with the user's reported medical concerns.

[5] https://huggingface.co/BAAI/bge-reranker-large

3.3 Generator: Generating Patient-Centered Medical Consultation

In the final stage, we generate medically accurate and context-aware responses using reranked documents. We fine-tune Llama2_{7B} (Touvron et al., 2023) and Llama3.1_{8B} on real medical consultation data, allowing the model to learn associations between patient queries and retrieved knowledge. Unlike methods that rely solely on synthetic prompts, our framework uses actual consultation records with retrieved documents integrated during fine-tuning. This helps the model better understand semantic relationships between queries and supporting knowledge, grounding its generation in clinically relevant context. As a result, ILlama can deliver more accurate and tailored responses while reducing hallucinations and speculative content.

4 Experiments

	HealthcareMagic	iCliniq
# dialogues	112,165	1,380
# tokens	27,475,545	313,735
Avg. # tokens per dialogue	245.01	227.34
Max # tokens per dialogue	2,544	1,001
Min # tokens per dialogue	78	60

Table 1: Statistics of the datasets used for training, validation, and testing, showing the distribution of dialogues and token counts.

4.1 Datasets

We use two types of data in ILlama, namely a UMLS-based KG and real-world medical consulta-

Category / Model	In-Distribution F1	METEOR	BLEU-4	ROUGE-2	PPL↓	Out-of-Distribution F1	METEOR	BLEU-4	ROUGE-2	PPL↓
Baselines without Retrieval										
$BART_{Large}$	0.837	0.059	0.0	0.038	**1.398**	0.838	0.063	0.0	0.023	**1.404**
$T5_{Large}$	0.840	0.061	0.0	0.031	1.475	0.843	0.069	0.0	0.020	1.417
$Llama2_{7B}$ w/ LoRA	0.838	0.192	0.031	0.052	7.940	0.838	0.201	0.029	0.050	10.926
$Llama3.1_{8B}$ w/ LoRA	0.844	0.230	0.061	0.074	10.659	0.841	**0.222**	0.029	0.048	14.259
Baselines without Fine-Tuning										
$Gemma2_{9B}$	0.836	0.180	0.016	0.036	19.211	0.841	0.201	0.022	0.040	16.648
$Yi1.5_{9B}$	0.832	0.168	0.015	0.034	15.552	0.835	0.188	0.021	0.038	14.371
$Falcon3_{7B}$	0.839	0.135	0.008	0.025	39.389	0.844	0.156	0.012	0.028	34.445
$DeepSeek\text{-}R1_{8B}$	0.832	0.175	0.012	0.028	43.653	0.837	0.191	0.014	0.030	40.259
Baselines with Fine-Tuning & Retrieval										
$Llama2_{7B}$ w/ LoRA	0.837	0.191	0.029	0.050	7.939	0.839	0.203	0.029	0.050	10.926
$Llama3.1_{8B}$ w/ LoRA	0.786	0.222	0.010	0.024	10.657	0.789	0.199	0.006	0.019	14.259
ChatDoctor	0.846	0.218	0.008	0.022	10.009	0.845	0.211	0.035	0.045	12.676
Ours										
$ILlama_{7B}$	0.866	0.203	0.037	0.058	7.939	0.851	0.213	**0.041**	0.048	10.924
$ILlama_{8B}$	**0.884**	**0.231**	**0.063**	**0.075**	7.659	**0.871**	**0.222**	0.030	**0.049**	10.259

Table 2: Performance comparison across baselines categorized into three groups: without retrieval, without fine-tuning, and with fine-tuning & retrieval. Metrics such as F1, METEOR, BLEU, ROUGE, and PPL are evaluated for both in-distribution and out-of-distribution datasets. The highlighted row represents our proposed method, demonstrating superior performance across most metrics.

tion records. The KG provides structured clinical relationships that support precise retrieval, while the consultation data enables response generation grounded in authentic patient–doctor interactions. Detailed descriptions of each dataset are provided in the following subsections.

4.1.1 Datasets for Medical Retrieval

We construct our KG using the 2024 release of the UMLS Metathesaurus[6], which comprises approximately 20K entities, 22 relation types, and 250K triples. This structured resource provides a semantic backbone for our RAG framework, enabling precise retrieval and integration of clinically relevant knowledge. Grounding generation in this KG enhances factual accuracy, reduces hallucinations, and supports context-aware medical responses.

4.1.2 Datasets for Medical Consultation

To evaluate the performance of ILlama, we used medical consultation records from two real-world platforms: HealthcareMagic and iCliniq. The HealthcareMagic dataset, specifically collected for medical question answering tasks, consists of single-turn interactions where each patient query is paired with a response from a licensed medical professional. We split this dataset into training, validation, and in-distribution test sets using an 8:1:1 ratio. In contrast, the iCliniq dataset, which follows a similar single-turn format, was used exclusively as an out-of-distribution test set. This separation allows us to evaluate the model's generalization performance on unseen queries from a different source, minimizing the risk of data leakage and ensuring a fair comparison. Both datasets are publicly available for academic research and have been de-identified to protect user privacy. As these records often include patient-reported details such as age and symptoms, the model implicitly learns to adapt responses to clinical contexts during fine-tuning. Detailed dataset statistics are provided in Table 1.

4.2 Metrics

We evaluated our model using semantic and quantitative metrics to assess the accuracy and contextual appropriateness of generated responses. For semantic evaluation, we adopted BERTScore (Zhang* et al., 2020) with $RoBERTa_{Large}$ (Liu et al., 2019), which measure contextual similarity using deep embeddings. This approach is particularly suitable for handling the nuances of medical language where lexical overlap is often limited (Hanna and Bojar, 2021). We report the F1 score from BERTScore as our primary semantic similarity metric.

In addition to semantic evaluation, we also employed lexical metrics such as ROUGE-2 (Lin, 2004), BLEU-4 (Papineni et al., 2002), Perplexity

[6] https://www.nlm.nih.gov/research/umls/licensedcontent/umlsknowledgesources.html

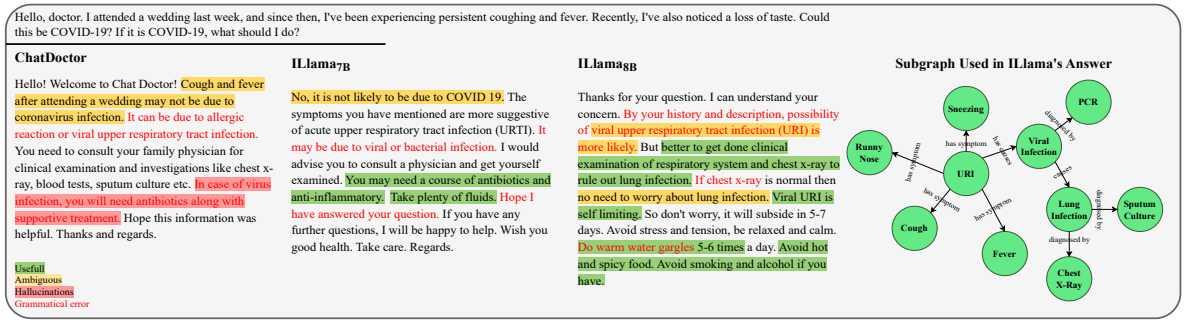

Figure 3: Comparison of responses from ChatDoctor, ILlama$_{7B}$, and ILlama$_{8B}$ regarding COVID-19 symptoms. Highlighted sections indicate usefulness, ambiguity, hallucinations, and grammatical errors.

(PPL) (Lavie and Agarwal, 2007), and METEOR to evaluate lexical accuracy, fluency, and coherence. In particular, METEOR considers synonymy, stemming, and paraphrasing, offering a flexible assessment of sentence-level similarity. This evaluation framework enables a comprehensive assessment of the model's ability to deliver precise, fluent, and contextually relevant medical responses.

4.3 Baselines

Baselines without Retrieval These models rely solely on fine-tuned capabilities on domain-specific data, without any retrieval mechanism. We examine BART$_{\text{Large}}$ (Lewis et al., 2020a), T5$_{\text{Large}}$ (Raffel et al., 2020), and Llama2$_{7B}$ w/ LoRA (Hu et al., 2022) and Llama3.1$_{8B}$ w/ LoRA.

Baselines without Fine-Tuning Models in this category use a retrieval mechanism but are not fine-tuned on domain-specific data. These baselines enhance their performance by leveraging the PubMed dataset (Xiong et al., 2024) for retrieval of pertinent biomedical literature, which provides a rich source of domain-specific information without the need for additional fine-tuning. These include Gemma2$_{9B}$ (Team et al., 2024), Yi1.5$_{9B}$ (Young et al., 2024), Falcon3$_{7B}$ (Team, 2024), and DeepSeek-R1$_{8B}$ (DeepSeek-AI et al., 2025).

Baselines with Fine-Tuning & Retrieval This category includes models that undergo fine-tuning on domain-specific data and use retrieval. Models include Llama2$_{7B}$ w/ LoRA (Hu et al., 2022), Llama3.1$_{8B}$ w/ LoRA, and ChatDoctor, although ChatDoctor does not use PubMed for retrieval.

4.4 Result

As shown in Table 2, ILlama consistently outperformed the baselines across both in-distribution and out-of-distribution evaluations. In the in-distribution setting, ILlama$_{8B}$ achieved the best F1 score of 0.884 and METEOR of 0.231, surpassing all baseline models. Notably, ILlama$_{7B}$ also showed strong performance (F1: 0.866, METEOR: 0.203), outperforming ChatDoctor, which shares the same base model, across all major metrics including F1, METEOR, and PPL. These results highlight the effectiveness of ILlama's RAG framework in producing accurate and coherent responses.

In the out-of-distribution setting, ILlama maintained robust generalization performance. ILlama$_{8B}$ achieved an F1 of 0.871 and METEOR of 0.222, with minimal performance drop compared to its in-distribution results. This demonstrates ILlama's ability to adapt to unseen queries and linguistic variations from different data sources. The integration of embedding-based vector retrieval and a structured medical KG played a key role in improving factual consistency while minimizing hallucinations. Overall, ILlama achieved state-of-the-art performance across F1, METEOR, and PPL, validating its reliability and generalization in real-world medical consultation scenarios.

5 Analysis

5.1 Qualitative Analysis of Outputs

As shown in Figure 3, we present a qualitative comparison of ChatDoctor, ILlama$_{7B}$, and ILlama$_{8B}$ in response to a COVID-19 related query, alongside the underlying reasoning represented through contextualized subgraphs extracted from the UMLS-based KG. While ChatDoctor exhibited frequent hallucinations, such as recommending antibiotics for viral infections, ILlama$_{7B}$ demonstrated improved clinical reasoning but still included unnecessary suggestions. ILlama$_{8B}$ provided the most balanced response, delivering accurate medical guid-

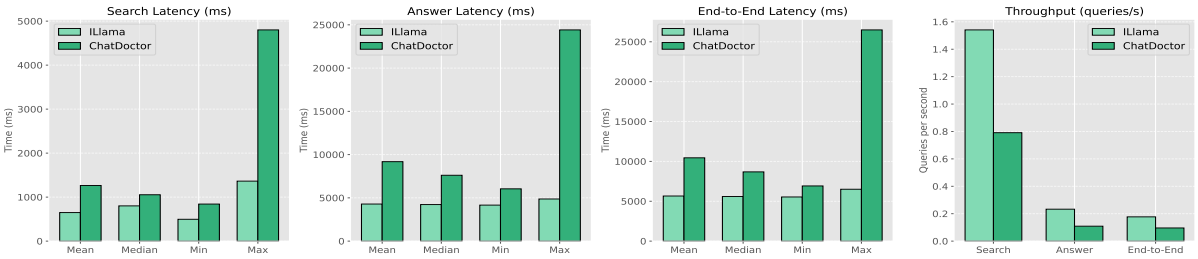

Figure 4: ILlama and ChatDoctor performance comparison in search latency, answer latency, end-to-end latency and throughput.

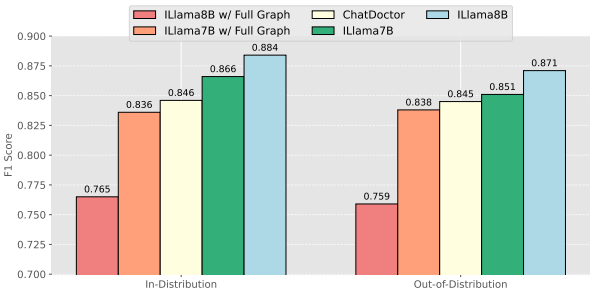

Figure 5: F1 score comparison between subgraph and full graph reasoning

ance and appropriate follow-up steps. These evaluations were conducted using the OpenAI o1 model[7] (Liu et al., 2023). The prompts used for this assessment are provided in Appendix D. The reasoning process is grounded in causal and diagnostic relationships (e.g., Viral Infection–URI–Cough/Fever or Chest X-Ray to rule out Lung Infection), captured within the subgraph structure.

5.2 Latency Analysis in Real-Time Medical Consultation Systems

In Figure 4, we present a comparison of latency and throughput between ILlama and ChatDoctor. ILlama consistently demonstrates lower latency across search, answer, and end-to-end processing. For example, ILlama's end-to-end latency ranges from approximately 5,538 to 6,507 ms, whereas ChatDoctor's ranges from around 6,921 to over 26,491 ms. This gap stems from ChatDoctor's reliance on LLM-based keyword extraction followed by live API calls to external sources such as Wikipedia, whose articles average more than 900 tokens and thus markedly inflate the answer-latency portion of the overall response time. In contrast, ILlama uses pre-indexed graph-based retrieval with documents averaging around 130 tokens, enabling higher throughput with reduced delay. These results highlight ILlama's efficiency and its suitability for real-time medical consultation.

5.3 Full-Graph vs. Subgraph Search

We compared the effectiveness of subgraph-based retrieval using Triple2Seq with that of a full-graph approach. As shown in Figure 5, the subgraph method produces more accurate and reliable responses. Full-graph retrieval, while comprehensive, often includes loosely connected or clinically irrelevant nodes, which can overwhelm the generation process with extraneous information and increase the risk of hallucinations. In contrast, subgraph retrieval narrows the focus to a central medical concept and its semantically related neighbors, allowing the model to process only the most relevant context. This targeted representation helps align retrieved knowledge more precisely with the user's query, resulting in improved factual accuracy and reduced noise. Such precision is particularly important in the medical domain, where irrelevant or overly broad context can compromise the safety and trustworthiness of responses.

6 Conclusion

In this study, we proposed ILlama, a retrieval-augmented medical consultation framework that integrates structured KGs and cross-encoder reranking. ILlama captures causal relationships between symptoms and diseases, and leverages patient demographics during training to support advice while reducing hallucinations. Experiments show strong performance across accuracy, latency, and contextual relevance in both in-distribution and out-of-distribution settings, highlighting the promise of structured medical knowledge in LLMs for scalable healthcare applications.

[7] https://openai.com/o1/

Limitations

Although ILlama improves the accuracy of medical consultations and reduces hallucinations by leveraging a UMLS-based KG and embedding-based retrieval, several limitations remain. First, the coverage of the KG and datasets is relatively narrow, primarily reflecting specific diseases and linguistic patterns. This limits the model's generalizability to broader clinical domains and multilingual, multicultural contexts. Expanding the training data to include more diverse and representative medical cases is necessary to improve robustness. Second, the KG may not capture the latest clinical updates such as emerging diseases, new treatments, or revised guidelines. Without real-time synchronization, the model may generate outdated or clinically irrelevant responses. Third, while ILlama achieves strong performance on standard metrics such as F1, METEOR, and PPL, these metrics do not fully capture clinical safety or decision-making validity. Future work should explore automated evaluation methods or deployment in simulated clinical environments to further validate the model's clinical reliability without increasing the burden on human experts. Lastly, the current system relies on relatively large-scale models, which may limit deployment in resource-constrained settings. Future directions include developing lightweight variants and adapting the framework for multilingual and cross-cultural applications to enable broader adoption in global healthcare environments.

Ethical Considerations

While our model, ILlama, aims to enhance medical consultations by reducing hallucinations and incorporating up-to-date medical knowledge, it is not 100% accurate and may not always provide correct diagnoses. In the medical field, inaccuracies can lead to severe consequences, including misdiagnosis and inappropriate treatment recommendations, which could potentially be life-threatening.

Therefore, it is crucial to acknowledge the limitations of AI-based medical consultation systems. Further research is necessary to improve the model's accuracy and reliability. Additionally, such systems should be used to support, not replace, professional medical advice. We recommend that users consult qualified healthcare professionals for personalized medical guidance and that our model be used as a supplementary tool to enhance access to medical information.

References

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A Implementation Details

This study fine-tuned a medical domain-specific model using LoRA with a configuration of $r = 16$, $lora\_alpha = 16$, and $lora\_dropout = 0$. The learning rate started at 2×10^{-5}, with 10% of the total steps dedicated to warmup. A linear scheduler was used for adjusting the learning rate during training. The model was trained for 3 epochs, and the maximum sequence length was set to 4,096 for handling complex queries, and the training was conducted on two NVIDIA RTX A6000 48GB GPUs.

For retrieval, 50 documents were fetched using maximum inner product search from the FAISS vector store. The top 10 documents from this set were selected for final use after reranking. This approach improved the model's ability to address medical queries by leveraging dense retrieval methods, enhancing both retrieval accuracy and response quality.

B Example Document from UMLS Subgraph

Table 3 presents an example of subgraph-to-text conversion used in our system. The subgraph is constructed around the central triple *(Lung cancer – has symptom – fatigue)* from the UMLS-based KG. All triples connected to the central node are included and expressed as simple natural language sentences using a rule-based template. Each relation type (e.g., *has symptom*, *diagnosed by*, *treated by*) is mapped to a consistent sentence pattern, such as "*X has symptom Y*" or "*X can be diagnosed by Y*." This consistency facilitates automatic transformation and retrieval in downstream components. The resulting document serves as a structured and semantically coherent unit of medical knowledge for training and inference.

C Objective Functions for Fine-Tuning the Medical Search System

C.1 Document-form Subgraph Encoder

The encoder is trained with the InfoNCE loss (Oord et al., 2018), which is a contrastive learning objective widely used in self-supervised learning. Given a set of N random samples $X = \{x_1, \ldots, x_N\}$ containing one positive sample x_{t+k} from the true conditional distribution $p(x_{t+k} \mid c_t)$ and $N-1$ negative samples drawn from a proposal distribution $p(x_{t+k})$, the loss is formulated as:

$$\mathcal{L}_N = -\mathbb{E}_X \left[\log \frac{f_k(x_{t+k}, c_t)}{\sum_{x_j \in X} f_k(x_j, c_t)} \right],$$

where $f_k(x, c_t)$ denotes a scoring function (e.g., a dot product or similarity function) that estimates the compatibility between context c_t and future sample x. Optimizing this loss leads $f_k(x_{t+k}, c_t)$ to approximate the density ratio:

$$f_k(x_{t+k}, c_t) \propto \frac{p(x_{t+k} \mid c_t)}{p(x_{t+k})}.$$

C.2 Reranker

The reranker model adopts a cross-encoder architecture and is fine-tuned with a binary cross-entropy loss. Given a query–document pair (q, d) and a binary label $y \in \{0, 1\}$ indicating relevance, the model predicts a scalar relevance score $\hat{y} = \text{sigmoid}(s(q, d))$, and the loss is computed as:

$$\mathcal{L}_{\text{BCE}} = -\left[y \log \hat{y} + (1 - y) \log(1 - \hat{y}) \right]$$

This objective encourages the model to produce high scores for relevant documents and low scores for irrelevant ones, improving the quality of the final ranking.

D Evaluation Prompt Design

To support the qualitative evaluation of model outputs, we designed three structured prompts targeting hallucination detection, grammatical correctness, and patient helpfulness. These prompts were used with the OpenAI o1 model to evaluate responses generated by ILlama. Table 5 presents the full text of each prompt. Each includes clear task instructions, placeholders for the model-generated response, and, in the helpfulness case, the original patient question. The prompts instruct the model to make a binary decision and identify specific parts of the response when relevant.

The hallucination prompt assesses whether a response contains fabricated or unsupported information. The grammatical prompt checks for language correctness. The helpfulness prompt determines whether the response includes content that would be useful to a patient, based on the given question. Evaluations were conducted in a zero-shot setting, and the prompt design aimed to guide the model toward accurate and consistent judgments without

fine-tuning. This allowed for scalable and focused assessment of clinical response quality.

E Algorithm

E.1 ILlama Algorithm

This algorithm, as shown in Algorithm 1, retrieves and reranks relevant documents for context-aware medical consultations. It combines FAISS search results, reranks them with a cross encoder, and generates a contextually accurate response using Llama, maintaining optimal performance and accuracy throughout the process.

E.2 Pseudo Query Generation Algorithm

This algorithm, as shown in Algorithm 2, generates patient-style queries and evaluates them to obtain (q, d) pairs for training the encoder and reranker if the conditions are met. Based on the input prompt and documents derived from the KG, the pseudo query generator (Llama3.1_{8B}) creates a query. The evaluator (Llama3.1_{8B}) then checks if the generated query meets the "patient-style" and "relevant" conditions. If the conditions are satisfied, the (q, d) pairs are stored for document-form subgraph encoder and reranker training; otherwise, the query is regenerated, and the evaluation process is repeated.

Subject	Relation	Object	Document-form subgraph
Lung Cancer	has symptom	Fatigue	Lung cancer has symptom fatigue.
Lung Cancer	has symptom	Shortness of Breath	Lung cancer has symptom shortness of breath.
Shortness of Breath	is symptom of	Anemia	Shortness of breath is symptom of anemia.
Fatigue	is symptom of	Anemia	Fatigue is symptom of anemia.
Lung Cancer	has symptom	Chronic Cough	Lung cancer has symptom chronic cough.
Lung Cancer	diagnosed by	Chest X-Ray	Lung cancer can be diagnosed by chest X-ray.
Lung Cancer	has cause	Smoking	Lung cancer has cause smoking.
Lung Cancer	has cause	Air Pollution	Lung cancer has cause air pollution.
Lung Cancer	treated by	Surgery	Lung cancer is treated by surgery.
Surgery	isa	lobectomy	Surgery is a lobectomy.

Table 3: Example of subgraph-to-text conversion for a document centered on the triple *(Lung cancer – has symptom – fatigue)*.

Prompting Category	Input Prompt
ILlama's prompt	You are a medical assistant specializing in providing expert consultations for medical inquiries.Your role is to deliver accurate, user-friendly medical information, clarify symptoms, explain potential medical conditions, and recommend next steps with empathy and professionalism. When formulating your response, to ensure clarity and accuracy, user-friendly answer in your response. ### Context {`context`} ### Input {`query`} ### Response

Table 4: Prompt used for ILlama inference

Algorithm 1 ILlama Algorithm for Medical Query Answering

Input:
q: User query
KG: UMLS-based KG
DB: FAISS vector database (Encoded Subgraph Documents)
$T2S$: Triple2Seq
QE: Query Encoder
CE: Cross Encoder
$Llama$: Llama Model
Output: Final response r
Step 1: UMLS-based KG Processing
$KG_{sub} \leftarrow T2S.split(KG)$
$D_{sub} \leftarrow$ Convert G_{sub} to text-based documents
Store D_{sub} in FAISS Vector Database
Step 2: Query Encoding
$q_{emb} \leftarrow QE.encode(q)$
Step 3: Retrieval & Reranking from Vector DB
$D_{top50} \leftarrow DB.retrieve(q_{emb}, k = 50)$
for each document d in D_{top50} **do**
    $s_d \leftarrow CE.score(q, d)$
end for
$D_{top10} \leftarrow$ Select top-10 documents based on s_d
Step 4: Response Generation
$input \leftarrow q + D_{top10}$
$r \leftarrow Llama.generate(input)$
Return r

Algorithm 2 Patient-Style Pseudo Query Generation and Evaluation

Input:
p: Prompt for query generation
d: Graph Document (Derived from KG)
QG: Query Generator (Llama3.1_{8B})
$Eval$: Evaluator (Llama3.1_{8B})
Output: (q, d) pairs for training Encoder and Reranker
Step 1: Generate Query
$q \leftarrow QG.generate(p, d)$
Step 2: Evaluate Query
$(s_1, s_2) \leftarrow Eval.check(q, d)$
if $s_1 ==$ Patient-Style **and** $s_2 ==$ Relevant **then**
    Store (q, d) for training Encoder and Reranker
else
    Regenerate q using QG
    Repeat from Step 2
end if
Return (q, d) pairs

Prompting Category	Input Prompt
Hallucination Evaluation	The following is a response generated by a model. Carefully read the response and evaluate whether it contains hallucinations based on logical consistency and factual accuracy. A hallucination refers to information that is fabricated or unsupported by evidence. ### Instructions - If a hallucination is found, pinpoint the exact part. - If no hallucination is found, respond with "No hallucination." ### Model Response: {`model response`} ### Evaluation:
Grammatical Error Evaluation	The following is a response generated by a model. Carefully read the response and identify any grammatical errors. ### Instructions - If grammatical errors are found, pinpoint the exact part. - If no grammatical errors are found, respond with "No grammatical errors." ### Model Response: {`model response`} ### Evaluation:
Helpful Information for Patients Evaluation	The following is a patient's question and a response generated by a model. Carefully read the response and identify any words or phrases that could be helpful to the patient. ### Instructions - Pinpoint the exact words or phrases in the model's response that are relevant to the patient's question. - If no helpful information is found, respond with "No helpful information." ### Patient's Question: {`question`} ### Model Response: {`model response`} ### Evaluation:

Table 5: Prompt for evaluation ILlama