NANYANG TECHNOLOGICAL UNIVERSITY SINGAPORE

Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly

WASP WALLENBERG AI, AUTONOMOUS SYSTEMS AND SOFTWARE PROGRAM

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Tan Tock Seng HOSPITAL

MedRAG: Enhancing Retrieval-augmented Generation with Knowledge Graph-Elicited Reasoning for Healthcare Copilot

Xuejiao Zhao[1,2*] Siyan Liu[1,2*] Su-Yin Yang[3] Chunyan Miao[1,2]

[1]Joint NTU-UBC Research Centre of Excellence in Active Living for the Elderly (LILY), NTU, Singapore

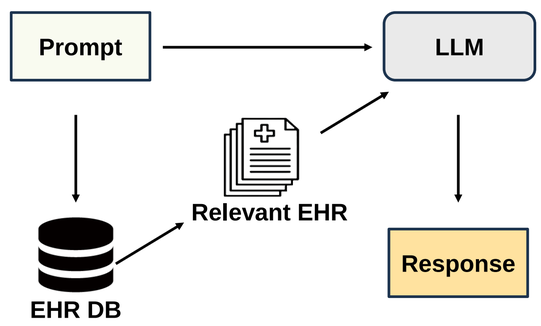
[3] Tan Tock Seng Hospital & Woodlands Health, Singapore

(* Co-first Author)

Retrieval-augmented Generation & Knowledge Graph

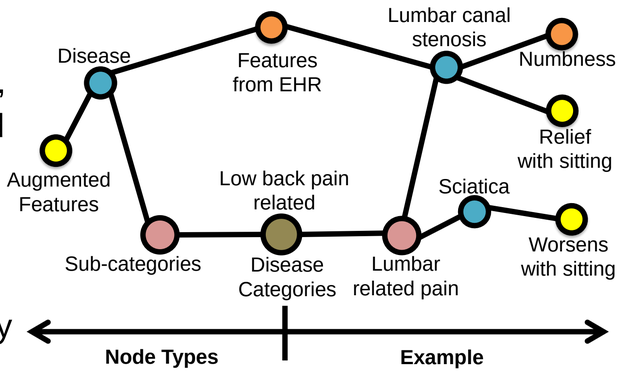
RAG (Retrieval-Augmented Generation):

- **Retrieves** relevant **local info** for **answer generation**
- **Improves** factuality and context-awareness of responses of LLMs
- **Suffers** from inaccuracies and vagueness due to heuristic-based approaches

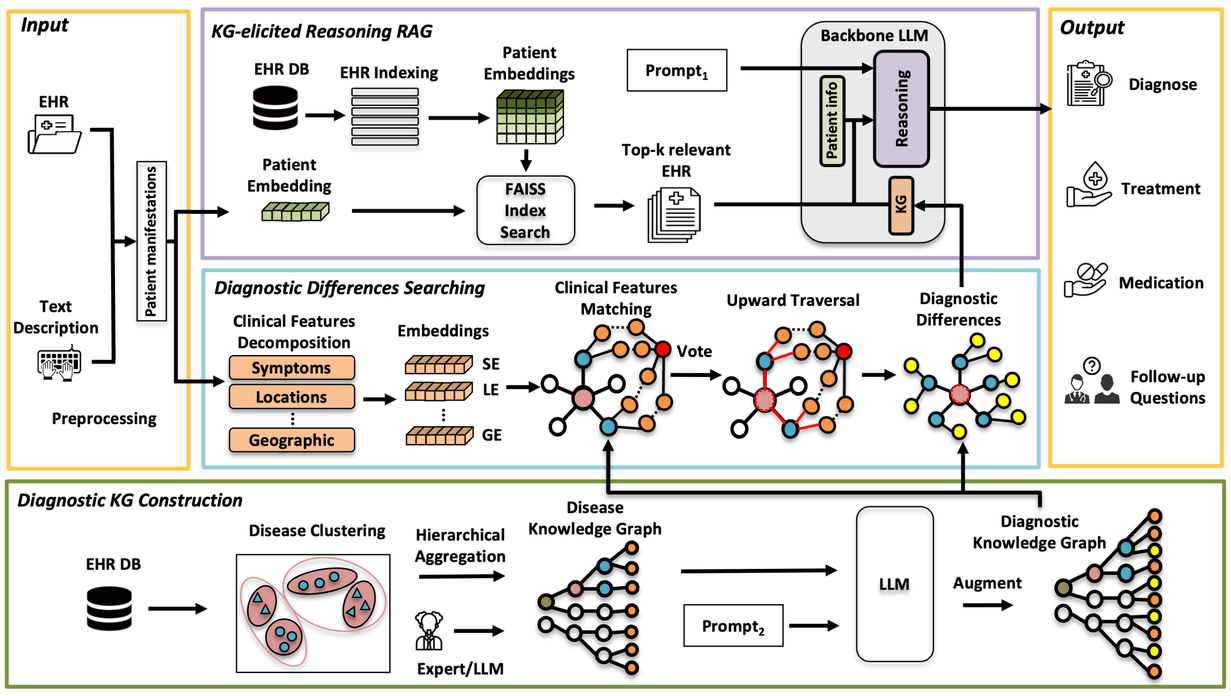


KG (Knowledge Graph):

- **Represents** medical entities (e.g., diseases, disease categories) and their relations
- **Elicits reasoning** of LLMs
- **Distinguishes** similar diseases and enhances diagnostic accuracy



Our Approach



1. Diagnostic Knowledge Graph (KG) Construction:

- **A four-tier diagnostic KG** is constructed through disease clustering, hierarchical aggregation and LLM augmentation from EHR database.

2. Diagnostic Differences KG Searching :

- **Patient symptoms** are matched to the diagnostic KG via clinical feature decomposition, matching, and upward traversal to identify key **diagnostic differences**.

3. KG-elicited Reasoning RAG :

- **Elicit LLM reasoning** based on the diagnostic difference KG, retrieved similar EHRs, and patient information to generate precise **diagnostic suggestions and proactive diagnostic questioning.**

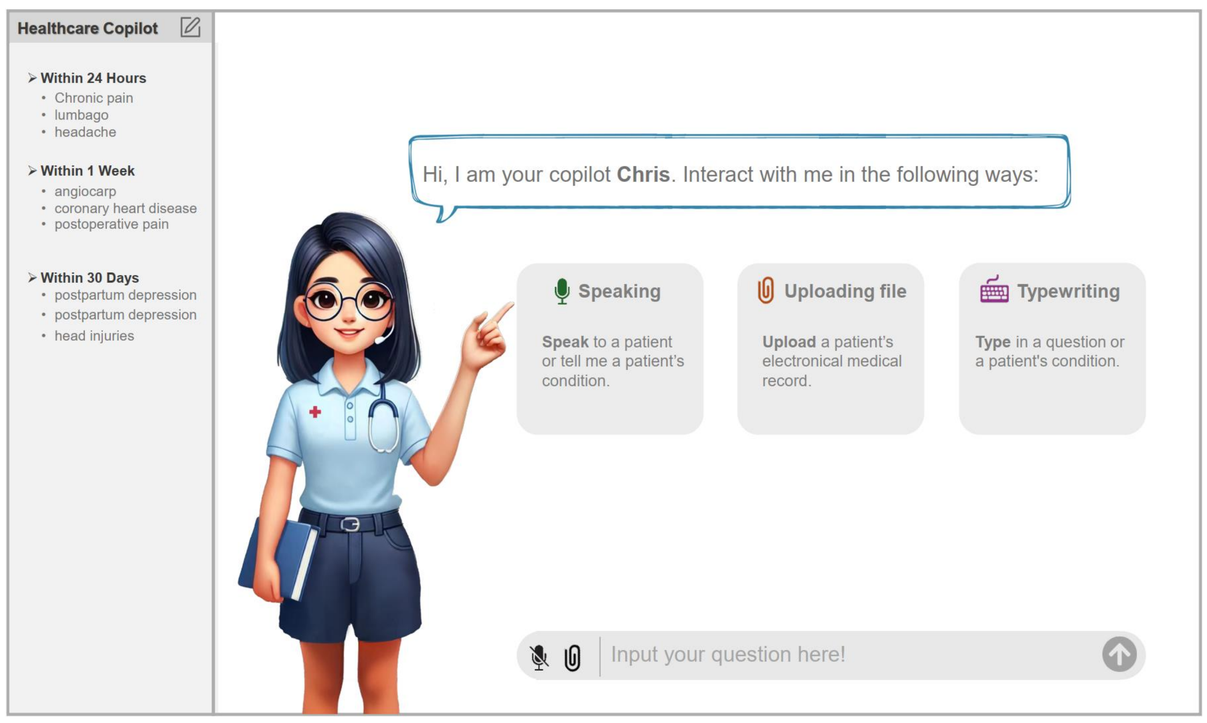
Evaluations and UI

	Backbone LLMs	Size	w/o KG-elicited Reasoning			w/ KG-elicited Reasoning		
			L1	*L2*	*L3*	*L1*	*L2*	*L3*
Open-source Models	Mixtral-8x7B	13B	60.38	32.08	22.34	84.62	82.69	63.46
	Qwen-2.5	72B	66.04	41.51	39.62	80.36	73.21	64.29
	Llama-3.1-Instruct	8B	75.47	54.72	43.40	79.25	75.47	66.04
	Llama-3.1-Instruct	70B	86.79	67.92	56.60	86.79	**83.02**	71.70
Closed-source Models	GPT-3.5-turbo	-	83.02	56.60	45.28	70.56	68.68	50.57
	GPT-4o-mini	-	88.68	67.92	56.60	85.85	75.00	60.38
	GPT-4o	-	**90.57**	**71.70**	**60.38**	**91.87**	81.78	**73.23**

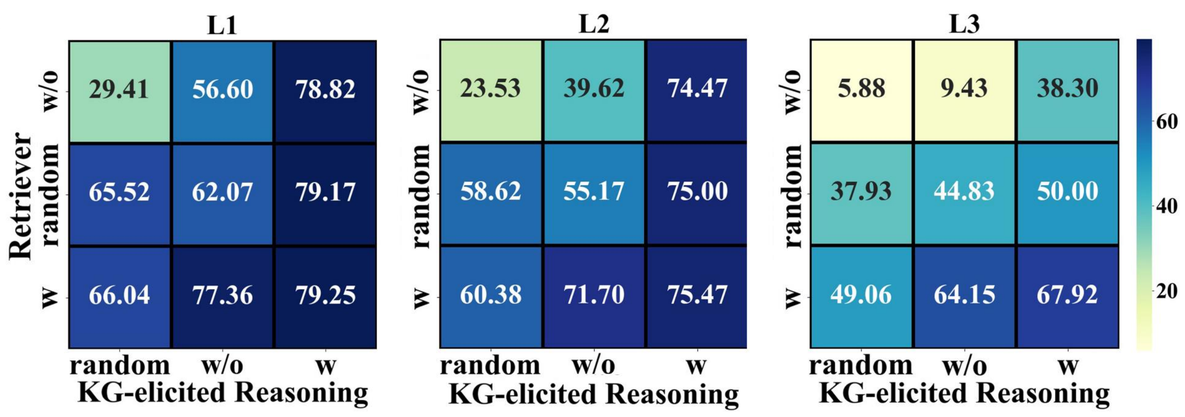
◆ **Performance of MedRAG on different LLM w and w/o KG-elicited reasoning**

Method	Model	CPDD			DDXPlus		
		L1	*L2*	*L3*	*L1*	*L2*	*L3*
Baselines	Naive RAG + COT	75.47	54.72	43.40	79.28	71.89	56.84
	FS-RAG	64.71	49.02	45.10	78.18	68.20	51.40
	FLARE	54.84	48.39	45.16	71.09	56.70	31.02
	FL-RAG	65.45	50.91	49.09	**90.12**	83.32	66.78
	DRAGIN	78.72	59.57	40.42	80.51	70.83	50.24
	SR-RAG	73.58	60.38	54.72	78.65	70.28	52.16
Ours	MedRAG	**79.25**	**75.47**	**66.04**	88.65	**83.46**	**68.01**

◆ **Outperform SOTA RAG methods on objective results**



◆ **UI of MedRAG – Healthcare Copilot**



◆ **Ablation study of KG-elicited reasoning (Llama-3.1-Instruct 8B &CPDD)**

Manifestation Masking Ratio	*L1*	*L2*	*L3*
100%	60.38	56.60	52.83
66.6%	69.39	67.35	55.10
33.3%	71.43	67.35	61.22
0%	79.25	75.47	66.04

◆ **Proactive diagnostic questioning**

Demo of MedRAG