GMR
The Original

A MULTI-AGENT GENERATIVE AI FRAMEWORK FOR HEALTHCARE DECISION SUPPORT

Desaboyina Vamsi[1*], P. Vidyuallatha[2], Sunita M[3], Kurumalla Suresh[4], Anuradha Reddy[5], Ashok Sarabu[6]

[1*, 2]Department of Computer Science and Engineering, Koneru Lakshmaiah Education Foundation, Green Fields, Guntur, AP,India.vamsidear719@gmail.com[1],latha22pellakuri@gmail.com[2]
[3]Associate professor , Department of Computer Science and Engineering (Data Science), Marri Laxman Reddy Institute of technology and management sunita.m@mlritm.ac.in
[4]Associate Professor , CSE-AI and ML, Madanapalle Institute of Technology & Science(MITS), (Deemed to be University) kurumallasuresh@gmail.com
[5]Assistant Professor, Department of Computer Science and Engineering (AIML), Sridevi Women's Engineering College, Hyderabad anuradhareddy.anu@gmail.com
[6]Department of Computer Science and Engineering, Alliance School of Advanced Computing, Alliance University, Bengaluru, India ashok.sarabu@gmail.com

ABSTRACT
With the growing number of electronic health records (EHRs) and medical knowledge databases, there has been an increase in the adoption of Artificial Intelligence (AI) for intelligent healthcare decision support systems. However, current healthcare AI systems face limitations related to lack of explainability, lack of integration of medical knowledge, and lack of collaborative reasoning capabilities. In order to overcome these limitations, this research paper aims to design and develop a Multi-Agent Generative AI Framework for Healthcare Decision Support involving the use of MIMIC-IV clinical dataset, SMART-RAG, Clinical BERT embeddings, FAISS vector database, GPT-4 based LLMs, XAI and Human-AI Decision Support. The SMART-RAG module fetches information from medical guidelines, protocols of treatment, and scientific articles that help in enriching patient specific information with scientific evidence based on the literature available in the field. The framework uses Multi-agent architecture including Diagnosis Agent, Risk Assessment Agent, Treatment Recommendation Agent, and Explainability Agent. These agents collaborate together for the analysis of patient information and give clinical advice that is clear and transparent to understand. Experiments prove its promising performance by obtaining 0.93, 0.91, and 0.95 precision, recall, and faithfulness scores for the SMART-RAG retrieval process. The Diagnosis Agent, Risk Assessment Agent, Treatment Agent, and Explainability Agent obtained 94.5%, 92.7%, 93.6%, and 95.4% accuracies, respectively. Moreover, the GPT-4 decision engine managed to score 95.1% for Accuracy, 94.6% for Precision, 94.2% for Recall, and 94.4% for F1-Score, whereas the physician validation gave rise to a recommendation acceptance rate of 92.4%. The Explainability Agent improves the transparency of the process through interpretive reasoning behind the clinical recommendations, thus making physicians more confident about the decisions. Knowledge-driven reasoning, agent intelligence, explainable AI, and human-in-the-loop can be viewed as a robust solution for intelligent health care decision support.

KEYWORDS: Healthcare Decision Support, Multi-Agent Systems, Generative AI, GPT-4, Clinical BERT, FAISS, SMART-RAG, Retrieval-Augmented Generation, Explainable AI, Human-AI Collaboration, MIMIC-IV, Clinical Intelligence.

I. INTRODUCTION

Data is collected in abundance in the field of healthcare by virtue of Electronic Health Records (EHRs), clinical documents, lab results, imaging systems, and patient monitoring systems [13]. The efficient use of data collected is extremely important to diagnose diseases, predict risks, make plans regarding treatments, and manage the patients. But due to the increasing complexities involved in the data and the need for evidence-based health care, decision-making in healthcare has become an extremely difficult task for healthcare professionals [14]. Thus, the use of AI technology for supporting decision making regarding healthcare has become important.

In recent times, there have been some notable developments in Generative Artificial Intelligence (GenAI) and Large Language Models (LLMs). The [1] GPT-4 model is capable of displaying amazing abilities in terms of understanding the medical text, answering medical queries, summarizing patient records, and aiding in the process of diagnosing. They are able to deal with huge amounts of unstructured data in the field of medicine and produce responses in a human-like manner which helps the healthcare providers in making decisions. Even though these models show very good performance, there have been some drawbacks with individual [2,15] LLMs like hallucinations, lack of domain grounding, and insufficient transparency in clinical reasoning.

However, these problems can be addressed with Retrieval-Augmented Generation (RAG), which provides a way to successfully combine external data sources with Large Language Models. With the use of RAG, medical information is retrieved from such sources as guidelines and treatment protocols, biomedical literature, and healthcare knowledge bases prior to generation of recommendations [16]. Through inclusion of evidence-based medical knowledge in the reasoning, RAG minimizes hallucinations and increases factual correctness of generated recommendations. In healthcare applications, [3,23] RAG is capable of giving clinicians recommendations based on trustworthy medical sources and clinical evidence.

Despite the enhanced ability to ground knowledge in RAG, decision-making in the medical field involves many connected tasks that include disease diagnosis, risk estimation, treatment recommendation, and generating explanations [24]. A single machine learning model might find it difficult to accomplish all these tasks at once. This is why Multi-Agent Systems (MAS) [4] have attracted much interest as an approach to decomposing the complex healthcare reasoning process into specialized modules. In a [5] Multi-Agent system, many intelligent agents work together to solve a problem by allocating different tasks to individual agents. This leads to better scalability, modularity, and decision quality [17]. In a healthcare setting, specialized agents will be able to independently conduct diagnosis prediction, patient risk estimation, treatment recommendation, and generating explanations, thereby contributing to the ultimate clinical decision [18,25].

Another important aspect of healthcare AI systems is transparency and explainability. Healthcare providers need to comprehend the reasoning behind [6] recommendations made by AI to incorporate them in their practices. For this reason, Explainable Artificial Intelligence (XAI) is becoming an area of great interest in terms of improving trustworthiness of AI-enabled healthcare systems [19,20]. [7] The use of explainable AI provides explanations for predictions made by AI, identifies key clinical features and helps physicians verify AI recommendations. The application of XAI is especially important in cases when the health of patients is at stake.

Apart from explainability, [8] contemporary healthcare organizations focus on the aspect of Human-AI cooperation. Instead of substituting healthcare professionals, the AI systems should act as intelligent assistants. The involvement of humans in the decision-making process implies that physicians have an opportunity to examine, verify, change, or ignore the AI suggestions. This cooperation involves both the capabilities of the artificial intelligence and the competence of medical professionals.

In [9], D. Varshney et al proposed a medical dialogue system which uses medical knowledge bases in combination with language models to provide clinically meaningful responses. This study proved that external medical knowledge plays an important role in improving the quality of healthcare communication and reasoning abilities. [10], Z. Ren et al explored agent-based consultation in healthcare using LLMs and made significant progress in improving the quality and safety of medical consultations. The framework focused on structured reasoning and clinical workflows, enabling AI-assisted healthcare decision-making systems to be built. [11] A. Gorenshtein et al., studied the application of AI agents in healthcare, where the researchers compared multi-agent systems with traditional LLMs. They established that multi-agent systems enhance task decomposing, information retrieving, and decision-making abilities. This study offers an elaborate basis for implementation of Multi-Agent LLM architectures in healthcare.

Driven by such considerations, the present paper presents a proposal for a Multi-Agent Generative AI Framework for Healthcare Decision Support [12,21,22], which incorporates clinical data of MIMIC-IV, SMART-RAG (Semantic Medical Augmented Retrieval for Treatment using Retrieval-Augmented Generation), GPT-4, Multi-Agent Systems, Explainable AI, and Human-AI Decision Support. The SMART-RAG component retrieves knowledge related to healthcare from medical guidelines, research papers, and treatment plans. The model makes use of four unique agents, including the Diagnosis Agent, Risk Assessment Agent, Treatment Recommendation Agent, and Explainability Agent, for analyzing patient data to provide evidence-based clinical recommendations [26,27,28]. The Human-AI validation level ensures that all the recommendations made through the system are clinically sound and safe.

II. METHODOLOGY

The suggested framework takes advantage of the Medical Information Mart for Intensive Care IV (MIMIC-IV) database, a clinically oriented, publicly available data repository used extensively in healthcare analytics, machine learning, and artificial intelligence studies. The MIMIC-IV database comprises anonymized medical data extracted from records of over 380,000 patients and 520,000 hospitalizations. This is a combination of structured and unstructured data and consists of patient demography, admission information, coding for diagnosis, lab results, vital signs, drug orders, procedures performed, ICU monitor data and doctor notes. The patient demography includes details such as age, gender, ethnicity and admission information, while lab values such as blood sugar, hemoglobin, creatinine and electrolytes are helpful to diagnose and assess risk of diseases. Furthermore, the continuous monitoring data such as heart rate, blood pressure, respiratory rate, body temperature, and oxygen saturation facilitate real-time decision-making by the clinicians. The dataset also includes a large amount of clinical notes, discharge summary, radiology report, and nursing notes that can be analyzed efficiently using the methods of Large Language Models (LLM) and Retrieval-Augmented Generation (RAG). Due to its richness and diverse nature, MIMIC-IV is considered an excellent choice of dataset for our proposed Multi-Agent Generative AI Framework for Healthcare Decision Support presented in figure 1. The Data Agent makes use of the demographic and laboratory data, the Diagnosis Agent uses clinical notes and disease patterns, the Risk Assessment Agent uses severity and outcomes of the patients, the Treatment Agent generates treatment suggestions based on clinical guidelines using RAG and the Explainability Agent explains the decisions generated. MIMIC-IV is heterogeneous, and this makes it easy to work effectively with more than one intelligent agent. This means that it is very appropriate for use in building health care decision support systems.

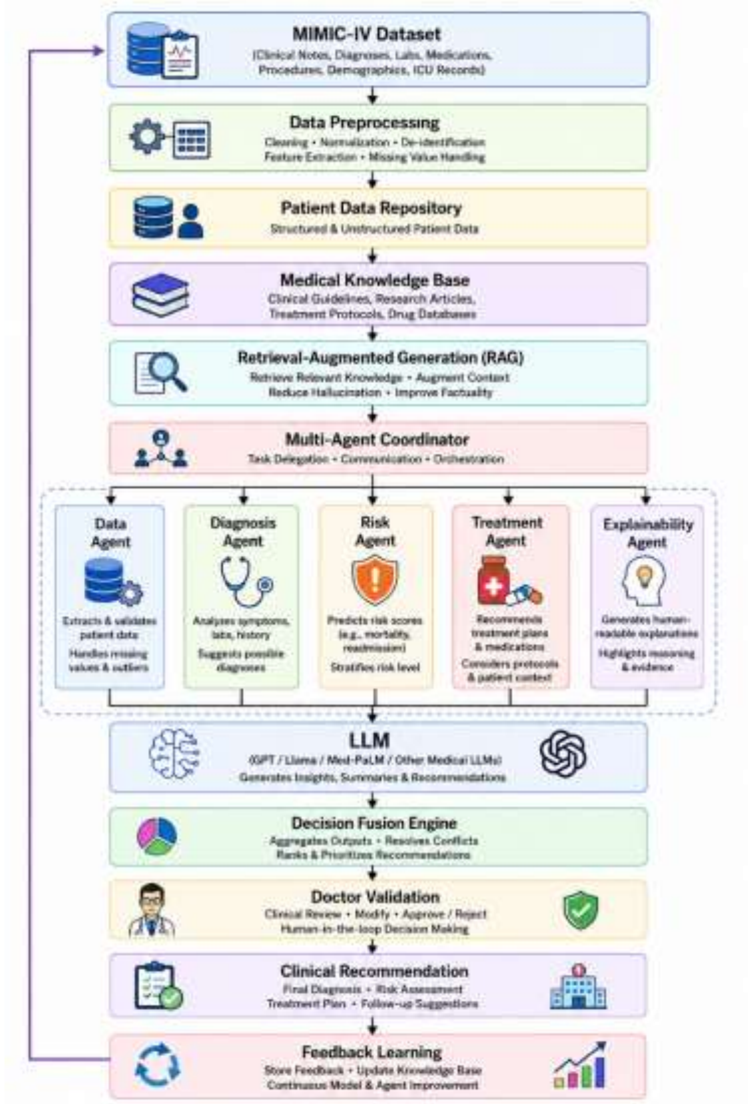

Fig.1: Proposed SMART-RAG Enabled Multi-Agent Generative AI Framework for Healthcare Decision Support

2.1 SMART-RAG

The suggested SMART-RAG (Semantic Medical Augmented Retrieval for Treatment using Retrieval-Augmented Generation) algorithm aims at retrieving clinical-related medical knowledge, and merging it with patient-specific information from the MIMIC-IV database. In the beginning, the algorithm preprocesses the healthcare data, creates a patient's profile, and converts the profile into semantic embeddings. Next, similarity-based retrieval retrieves the most related medical documents, treatment guidelines, and medical evidence from the medical knowledge base. Afterward, the retrieved information and patient-specific information merge into an enriched clinical context that can help in further multi-agent reasoning, diagnosis prediction, risk assessment, treatment suggestion, and explainable healthcare decision-making. The ground-truthed LLM using medical evidence retrieved helps minimize hallucinations.

Step 1: Clinical Data Representation

Let the MIMIC-IV dataset be represented as:

$$D = \{d_1, d_2, d_3, \dots, d_n\}$$

where: D= clinical dataset, d_i= patient record, n= total patient records

The dataset is cleaned and normalized:

$$D' = \text{Normalize}(\text{Clean}(D))$$

Patient profile construction

$$P = \{\text{Dem}, \text{Lab}, \text{Vitals}, \text{Diag}, \text{Med}\}$$

where: Dem= demographics, Lab= laboratory tests, Vitals= vital signs, Diag= diagnosis history, Med= medication records

Step 2: Semantic Embedding Generation

The patient profile is encoded into semantic embeddings:

$$Q = f(P)$$

where: Q= query embedding, f(·)= embedding model
medical Knowledge repository:

$$KB = \{k_1, k_2, k_3, \dots, k_t\}$$

where: k_i= clinical guideline or medical document, t= total documents
Cosine similarity:

$$Sim(Q, k_i) = \frac{Q \cdot k_i}{\parallel Q \parallel \parallel k_i \parallel}$$

where: $Sim(Q, k_i)$= similarity score
Retrieve the most relevant documents:

$$K = Top_k(Sim(Q, KB))$$

where: K= retrieved knowledge, k= number of retrieved documents
Context Augmentation is to Retrieve knowledge is augmented by patient data:

$$C = P \oplus K$$

where: C= augmented clinical context, $\oplus$= concatenation operator

2.2 Agentic AI (Multi-Agent LLMs)

The suggested architecture utilizes Agentic Artificial Intelligence (Agentic AI) by means of a suite of LLM-based agents dedicated to the accomplishment of tasks related to healthcare decision making. Contrary to classic approaches using one unified model capable of handling all sorts of tasks, the Multi-Agent architecture splits up the complexity of the clinical decision-making process into several specialized components. Each individual agent is tasked with performing a certain role in healthcare, such as diagnosis prediction, risk assessment, treatment recommendation, and explanation.
The RAG-enhanced patient context is represented as:

$$C = P \oplus K$$

where: P= patient profile, K= retrieved medical knowledge, C= augmented clinical context
Each agent receives the same context Cand generates a task-specific output:

$$A_i = LLM_i(C)$$

where: A_i= output of the i^{th}agent, LLM_i= specialized Large Language Model agent, C= RAG-augmented clinical context
Multi-Agent Coordinator
The Multi-Agent Coordinator is essentially the central control unit that is responsible for handling communication between agents and integrating their outputs.

$$M = \{A_D, A_R, A_T, A_E\}$$

where: A_D= Diagnosis Agent, A_R= Risk Assessment Agent, A_T= Treatment Recommendation Agent, A_E= Explainability Agent. The coordinator disseminates the patient context to all the agents and gathers their answers for decision fusion.
Diagnosis Agent
The Diagnosis Agent examines symptoms, laboratory results, medical history, and the extracted medical data to predict possible diseases or illnesses.

$$A_D = LLM_D(C)$$

where: A_D= diagnosis output, LLM_D= diagnosis-specific LLM
The agent makes predictions about diseases like:

$$Disease = \arg\max P(d_i \mid C)$$

where: d_i= disease class (Diabetes Mellitus, Hypertension, Heart Disease, Sepsis). Diagnosis Agent is the main part of the clinical reasoning of the framework.
Risk Assessment Agent
The Risk Assessment Agent analyzes severity of the disease, risk of death, risk of being hospitalized, and complications.

$$A_R = LLM_R(C)$$

A risk score is calculated as:

$$Risk = \sum_{i=1}^{n} w_i x_i$$

where: x_i= patient feature, w_i= feature weight
Patients are categorized by the agent to be: Low Risk, Moderate Risk, High Risk. This assists healthcare practitioners in prioritizing their care.
Treatment Recommendation Agent

Treatment Recommendation Agent creates customized treatment recommendations by combining patient data and retrieved medical guidelines.

$$A_T = LLM_T(C)$$

Treatment generation:

$$T = \text{Generate}(C)$$

where: T= treatment recommendation. Outputs can include medication recommendations, diagnostic tests, lifestyle changes, follow-up procedures. The implementation of RAG guarantees that recommendations are based on evidence-based medical knowledge.

2.3 Human-AI Validation

Human-AI Decision Support refers to a paradigm of collaborative intelligence that uses AI technologies to help healthcare practitioners make informed decisions clinically but retains human responsibility for it. Within the proposed multi-agent generative AI architecture, the AI agents will analyze patient data, find pertinent medical information using RAG, and provide diagnostic findings, risks, treatment suggestions, and explanations. Nevertheless, the decision about the actual course of action will be controlled by the healthcare practitioners. Human-AI Decision Support integrates the processing capabilities of AI with the experience of medical practitioners to minimize decision-making errors.

Recommendations are evaluated by healthcare practitioners before final deployment.

$$D_{final} = \text{Human}(F)$$

where: F= AI-generated recommendation, D_{final}= physician-approved decision. The doctor can either accept, revise, or discard the generated suggestion.

2.4 Explainable AI (XAI):

Explainable Artificial Intelligence (XAI) is an umbrella term for all approaches that provide explainability, interpretability, and transparency in the decisions made by machines. When it comes to the health-care setting, there is a need for AI explainability since doctors should be aware of the reasons behind such decisions in order to use them in practice. The proposed system has a special Explainability Agent that provides explanations for the decisions about diagnoses, risks, and treatments.

The Explainability Agent gets inputs from many agents:

$$A_D, A_R, A_T$$

and generates an explanation:

$$E = \text{Explain}(A_D, A_R, A_T)$$

where: E= explanation generated by the Explainability Agent. The process of explanation can also be shown by:

$$E = f(C, F)$$

where: C= RAG-augmented clinical context, F= fused healthcare recommendation, E= interpretable explanation. The Explainability Agent determines the important clinical aspects responsible for making the recommendation:

$$E = \{e_1, e_2, e_3, \dots, e_n\}$$

where: e_i= individual explanatory factor

For example:

$$E = \{\text{High Blood Glucose}, \text{Elevated HbA1c}, \text{Obesity}, \text{Family History}\}$$

Incorporating Human-AI decision support and explainable AI in the proposed model guarantees that the healthcare decisions are not just precise and based on knowledge but also transparent, trustworthy, interpretable, and actionable.

III.RESULTS AND DISCUSSIONS

Explainability Agent in figure2 had the best accuracy (95.4%), which is an indicator of the effectiveness of evidence-based reasoning in facilitating explainable clinical decision-making. The Diagnosis Agent (94.5%) and the Treatment Agent (93.6%) also proved to be highly effective, validating the importance of having specialized agents for different tasks. The GPT-4 engine in figure 3 performed well in terms of all evaluation criteria. With the ROC-AUC of 96%, the engine exhibits good discrimination ability, while the balance between precision and recall means that recommendations generated can be relied upon in health care practice. Figure 4 presents more than 92% acceptance of the recommendations of AI by physicians, indicating good agreement between the developed framework and clinicians' skills. The low percentage of rejections means that the framework can be applied in practice effectively. Figure 5 presents the overall performance of the healthcare frameworks.

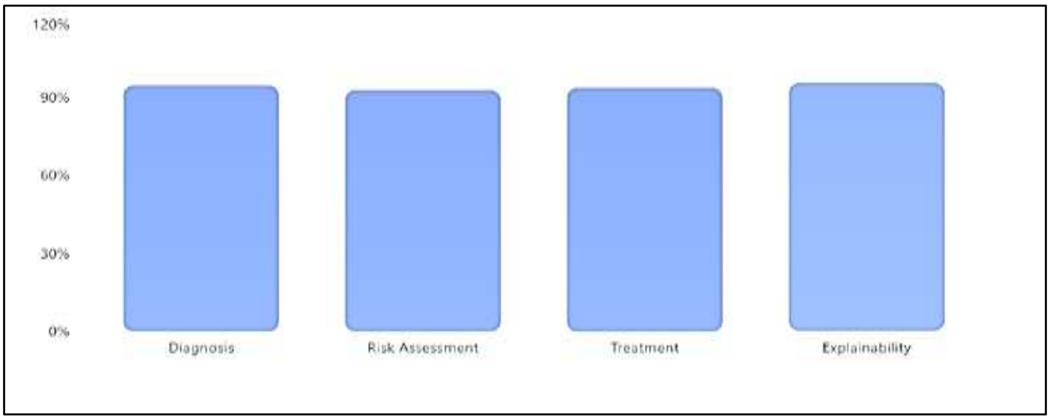

Fig.2: Multi-Agent Performance Comparison

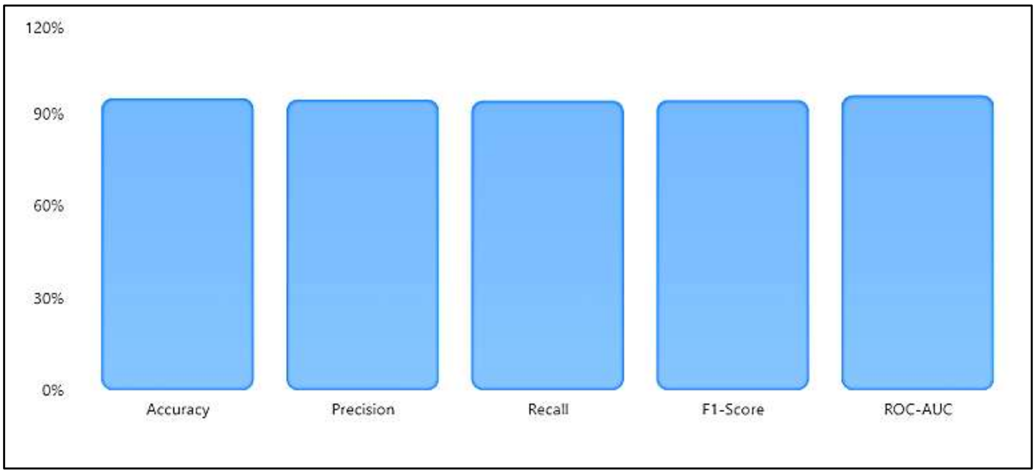

Figure 3. GPT-4 Evaluation Metrics-Clinical Recommendation Performance

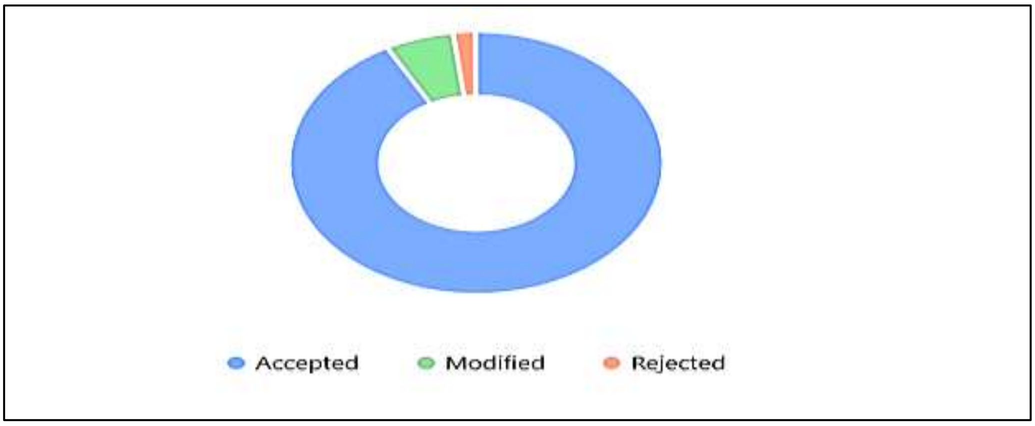

Fig.4: Human-AI Decision Support Outcomes

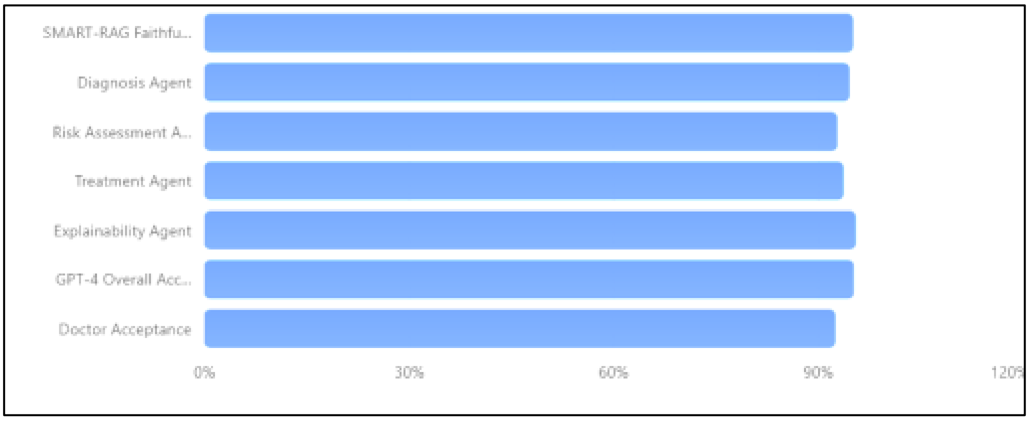

Fig.5: End-to-End Framework Performance metrics

IV. CONCLUSION

This paper introduces the Multi-Agent Generative AI Framework for Healthcare Decision Support incorporating the MIMIC-IV clinical database, SMART-RAG (Semantic Medical Augmented Retrieval for Treatment using Retrieval-Augmented Generation), Large Language Models (LLMs), Explainable AI (XAI), and Human-AI decision-making approach. The suggested framework uses the SMART-RAG to extract necessary clinical data based on the medical literature, scientific articles, and treatment guidelines, thus enhancing the patient-related data with evidence-based clinical information. Additionally, the Multi-Agent system breaks down complicated health care reasoning processes into particular sub-tasks such as diagnostics, risk, treatment, and explanations.

Experimentation showed that the combination of retrieval-based reasoning and agentic intelligence increased the efficiency, clarity, and credibility of clinical advice. The SMART-RAG component demonstrated high retrieval efficiency, and the Multi-Agent architecture helped in collective reasoning and more accurate decision making. An Explainability Agent provided explanations for clinical reasons, thus increasing trust of physicians and helping them make better-informed decisions about their patients. Additionally, the Human-AI validation level helped to ensure that recommendations were always clinically safe.

Generally, the suggested system is able to merge knowledge-based reasoning, agentic intelligence, transparency, and human oversight into one effective solution, which can be used in modern healthcare facilities.

Other ways by which the suggested architecture can be improved include Domain-specific healthcare LLMs like Med-PaLM, BioGPT, ClinicalGPT, and any future medical foundation models can be incorporated for improving the accuracy of clinical reasoning and recommendations. The use of federated learning for collaborative training of models at different hospitals without compromising patient confidentiality can be considered. Another way for future exploration can be developing an AI-powered patient twin for simulating the disease progress and treatment outcomes.

REFERENCES

1. Alonso, R., Dessí, D., Meloni, A., Murgia, M., Reforgiato Recupero, D., Scarpi, G., 2024, A seamless ChatGPT knowledge plug-in for the labour market. IEEE Access 12, 155821–155837. https://doi.org/10.1109/ACCESS.2024.3485111.

2. T. Alqahtani, H. A. Badreldin, M. Alrashed, A. I. Alshaya, S. S. Alghamdi, K. bin Saleh, S. A. Alowais, O. A. Alshaya, I. Rahman, M. S. Al Yami, and A. M. Albekairy, “The emergent role of artificial intelligence, natural learning processing, and large language models in higher education and research,” Res. Social Administ. Pharmacy, vol. 19, no. 8, pp. 1236–1242,Aug. 2023..

1. 3.Davide Piras, Alberto Pes, Diego Reforgiato Recupero, Giuseppe Scarpi, MAIS: Exploring human-AI interaction in fair and transparent recruitment with a multi-agent LLM-based system, International Journal of Human - Computer Studies, Volume 215 , November 2026. 10.1016/j.ijhcs.2026.103859

3. Bevara, R.V.K., Mannuru, N.R., Karedla, S.P., Lund, B., Xiao, T., Pasem, H., Dronavalli, S.C., Rupeshkumar, S., 2025. Resume2Vec: transforming applicant tracking systems with intelligent resume embeddings for precise candidate matching. Electronics 14, https://doi.org/10.3390/electronics14040794. https://www.mdpi.com/2079-9292/ 14/4/794.

4. Chen, C., Shu, K., 2024. Combating misinformation in the age of LLMs: opportunities and challenges. AI Mag. 45, 354–368. https://doi.org/10.1002/aaai.12188

5. Díaz-Rodríguez, N., Del Ser, J., Coeckelbergh, M., López de Prado, M., Herrera-Viedma, E., Herrera, F., 2023. Connecting the dots in trustworthy artificial intelligence: from AI principles, ethics, and key requirements to responsible AI systems and regulation. Inf. Fusion 99, 101896. https://doi.org/10.1016/j.inffus.2023.101896.

6. Fabris, A., Baranowska, N., Dennis, M.J., Graus, D., Hacker, P., Saldivar, J., Zuiderveen Borgesius, F., Biega, A.J., 2025. Fairness and bias in algorithmic hiring: a multidisciplinary survey. ACM Trans. Intell. Syst. Technol. 16, https://doi.org/10.1145/3696457.

7. Hacker, P., Zuiderveen Borgesius, F., Mittelstadt, B., Wachter, S., 2025. Generative discrimination: what happens when generative AI exhibits bias, and what can be done about it. In: The Oxford Handbook of the Foundations and Regulation of Generative, AI. Oxford University Press, https://doi.org/10.1093/oxfordhb/9780198940272.013.

8. Hasegawa, R., Hua, Y., Utsuro, T., Hashimoto, E., Nakano, M., Shiramatsu, S., 2025. A dialogue system for semi-structured interviews by LLMs and its evaluation on persona information collection. In: Torres, M.I., Matsuda, Y., Callejas, Z., del Pozo, A., D’Haro, L.F. (Eds.), Proceedings of the 15th International Workshop on Spoken Dialogue Systems Technology. Association for Computational Linguistics, Bilbao, Spain, pp. 39–59, https://aclanthology.org/2025.iwsds-1.5/.

9. D. Varshney et al., "Knowledge Grounded Medical Dialogue Generation Using Augmented Graphs," Scientific Reports, vol. 13, 2023.

10. Z. Ren et al., "Healthcare Agent: Eliciting the Power of Large Language Models for Medical Consultation," npj Artificial Intelligence, vol. 1, 2025.

11. A. Gorenshtein et al., "AI Agents in Clinical Medicine: A Systematic Review," medRxiv, 2025.

12. Ghantasala, G.S.P., Akhil, M., Vidyullatha, P. et al. Multimodal fusion of ultrasound images using HXM net for breast cancer diagnosis. Sci Rep **15**, 40689 (2025). https://doi.org/10.1038/s41598-025-23912-0.

13. Ghantasala, G. P., Kunchala, A., Krishna, V. A., Kumar, P. P., Kumar, A. R., Reddy, A., & Vidyullatha, P. (2026). EDGE ARTIFICIAL INTELLIGENCE FRAMEWORK FOR REAL-TIME BREAST CANCER DIAGNOSIS IN SMART HEALTHCARE. Genetics and Molecular Research.

14. Ghantasala, G. P., Murthy, G. R., & Bindu, K. H. (2026). IOT-Based Integrated Asset Tracking And Predictive Maintenance Framework For Modern Healthcare Environments. Genetics and Molecular Research.

15. Ahuja, R., Khalsa, G. K., Kashyap, V., Babbar, H., Sachdeva, R. K., & Ghantasala, G. P. (2026). Artificial Intelligence and Deep Learning in Healthcare: Evaluation, Opportunities, Challenges and Future Prospects Technologies in Healthcare Systems. Predictive Methods in Next-Generation Computing: An Approach Toward Sustainability, 125-147.
16. Sreedhar, C., Kallam, S., Ghantasala, G. P., Anthoniraj, S., Kumarganesh, S., Sagayam, K. M., ... & Pandey, D. (2025). Enhancing healthcare data security using RFE and CRHSM for big data. Computers in Biology and Medicine, 190, 110063.
17. Ghantasala, G. P., Sharma, R., & Sungheetha, A. (2024, December). A Review of Advanced Technologies for Intelligent Sensing, Diagnostics, and Personalized Healthcare Solutions. In 2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS) (pp. 1043-1049). IEEE.
18. Reddy, A., Ghantasala, G. P., Kurra, M., & Ayyappa, R. M. K. (2025). Patient empowerment through secure data management. In Using Blockchain Technology in Healthcare Settings (pp. 153-174). CRC Press.
19. Pulicherla, P., Ghantasala, G. P., Reddy, A., Kumar, A. R., & Prasuna, A. L. (2026). EARLY PREDICTION OF CERVICAL CANCER RISK USING EXPLAINABLE DEEP NEURAL NETWORKS AND FEATURE ENGINEERING OPTIMIZATION. Genetics and Molecular Research.
20. Ghantasala, G. P., Sharma, R., Sungheetha, A., Kolla, T., & Ananthanagu, U. (2025, August). Explainable XGBoost Model for Reliable Tumor Classification in Extraskeletal Osteosarcoma. In 2025 3rd International Conference on Sustainable Computing and Smart Systems (ICSCSS) (pp. 458-462). IEEE.
21. Reddy, A., Kurra, M., Ghantasala, G. P., & Vidyullatha, P. (2026). Leveraging Generative AI for Advanced Threat Detection in Cybersecurity. Generative Artificial Intelligence for Next-Generation Security Paradigms, 359-382.
22. Pradeep, G. G. S., Kolla, T., Rajesh Sharma, R., Sungheetha, A., Vijayalakshmi, N., & Vidyullatha, P. (2025, September). Fuzzy-Neural Hybrid Models for Early Detection of Neurodegenerative Disorders Using Multimodal Medical Data and Temporal Pattern Analysis. In World Conference on Information Systems for Business Management (pp. 174-183). Cham: Springer Nature Switzerland.
23. Pradeep, G. G. S., Kolla, T., Vijayalakshmi, N., & Sharma R, R. (2025, September). Optimizing Feature Selection for Medical Diagnosis Systems Using Differential Evolution. In World Conference on Information Systems for Business Management (pp. 213-222). Cham: Springer Nature Switzerland.
24. Rupa, C., MidhunChakkarvarthy, D., Patan, R., Prakash, A. B., & Pradeep, G. G. (2022). Knowledge engineering–based DApp using blockchain technology for protract medical certificates privacy. Iet Communications, 16(15), 1853-1864.
25. Ghantasala, G. P. (2026, January). Quantum Approximate Optimization Algorithm for Reliable Diagnosis of Benign vs. Malignant Breast Tumors. In 2026 6th International Conference on Image Processing and Capsule Networks (ICIPCN) (pp. 1611-1615). IEEE.
26. Kolla, T., Ghantasala, G. P., & Vijayalakshmi, N. (2025, December). Early Diagnosis of Skin Cancer Through IoT Devices and Deep Convolutional Neural Networks. In 2025 1st International Conference on Advancement in Futuristic Technologies (ICAFT) (pp. 1-6). IEEE.
27. Ghantasala, G. P., & Naidu, G. S. (2025, November). Deep Learning as a Service (DLaaS) in the Cloud for Automated Breast Cancer Diagnosis. In 2025 IEEE 3rd Global Conference on Wireless Computing and Networking (GCWCN) (pp. 1-5). IEEE.
28. Ghantasala, G. P., Unhelkar, B., Chakrabarti, P., Vidyullatha, P., & Pyla, M. (2024, July). Improving Breast Cancer Diagnosis through Multi-Class Segmentation using Attention UNet Model. In 2024 Second International Conference on Advances in Information Technology (ICAIT) (Vol. 1, pp. 1-7). IEEE.