International Journal of Advances in Applied Computational Intelligence

♦ ISSN: 2833-5600 Vol: 08, No. 01, 2026 ♦ PP. 33–41

Article DOI: https://doi.org/10.54216/IJAACI.080105

FULL LENGTH ARTICLE

# Agentic Generative AI Framework for Intelligent Disease Prediction and Clinical Decision-Making in Smart Healthcare

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Received: January 05, 2026 Revised: February 10 2026 Accepted: March 19, 2026 ⋆ Corresponding author

## ABSTRACT

Rapid growth in the adoption of Electronic Health Records (EHRs), Internet of Medical Things (IoMT) devices, wearable sensor technology, and digital healthcare systems offers immense scope for intelligent healthcare decision support. However, most AI-enabled healthcare systems in use today still lack explainability, contextual reasoning capabilities, and effective decision-making. For these reasons, this research develops an Agentic Generative AI Framework for Intelligent Disease Prediction and Decision-Making in smart healthcare. The framework incorporates predictive analytics, Generative AI-based clinical reasoning, and autonomous intelligent agents into a coherent healthcare framework. Six specific agents are used for data gathering, data analysis, disease prediction, clinical reasoning, treatment recommendations, and patient monitoring. The combined functionality of these agents supports disease prediction, clinical reasoning, and personalized treatment plans. Evaluation was performed on healthcare datasets related to heart disease, diabetes, chronic kidney disease, and breast cancer. Experimental results show high efficiency, stable accuracy across diseases, reliable recommendation generation, and enhanced healthcare intelligence compared with traditional ML, DL, and LLM methods. Results show that combining Agentic AI with Generative AI increases explainability, adaptability, and efficiency in medical decision support. The proposed model represents an encouraging path toward intelligent, patient-centered, and explainable smart healthcare systems.

**Keywords:** Agentic Artificial Intelligence ▪ Generative Artificial Intelligence ▪ Disease Prediction ▪ Clinical Decision Support ▪ Explainable AI ▪ Smart Healthcare

## 1. INTRODUCTION

The healthcare industry has undergone a revolution in its use of technology with the introduction of Electronic Health Records (EHRs), Internet of Medical Things (IoMT) devices, wearables, medical imaging equipment, and cloud computing platforms. These systems produce large amounts of health data that can support diagnosis, treatment, and disease management. Artificial Intelligence has become an important part of data interpretation and evidence-based clinical decision-making. Machine learning and deep learning models have been successful in disease prediction, image analysis, and patient outcome forecasting.

Despite these improvements, many currently available AI-driven health systems concentrate mainly on prediction and lack explainability and adaptability. In healthcare settings, decision-making needs transparency, accountability, and the use of multiple medical knowledge sources. Predictive models often work in isolation and therefore provide limited support for the complete process of diagnosis and treatment.

Innovations in Generative Artificial Intelligence and Large Language Models (LLMs) have increased the functionality of intelligent healthcare applications. Such models can comprehend medical terminology, synthesize clinical knowledge, generate explanations, and help diagnose illnesses. Modern language models have demonstrated medical knowledge and reasoning ability, indicating that Generative AI can support clinical decision-making, healthcare delivery, and knowledge acquisition.

Agentic Artificial Intelligence has also emerged as an approach for autonomous decision-making. Agentic AI systems can sense information, reason about goals, plan actions, and cooperate with other agents to perform complex processes. In medicine, agentic AI can facilitate disease prediction, clinical reasoning, treatment suggestions, and ongoing patient surveillance through coordination among different agents.

The integration of Agentic AI and Generative AI offers a promising path toward a sophisticated healthcare ecosystem. Through collaboration between these models, reliable prediction results, appropriate explanations, medical data acquisition, and personalized decision-making can be achieved. Retrieval-based solutions and specialized domain knowledge can further improve the accuracy of AI suggestions.

### 1.1 Evolution of Artificial Intelligence in Healthcare

AI for healthcare has developed from expert rule-based systems to machine learning, deep learning, and, more recently, generative AI frameworks. Early clinical decision support systems used preprogrammed rules and knowledge databases. Machine learning introduced data-driven prediction models, while deep learning enabled accurate disease detection and image analysis. Generative AI and LLMs have recently made reasoning and knowledge synthesis possible in healthcare.

### 1.2 Role of Agentic Generative AI in Smart Healthcare

The Agentic Generative AI framework integrates decision-making skills with the reasoning and knowledge-creation capabilities of large language models. In an intelligent healthcare setting, specialized agents can work together to gather patient information, analyze clinical data, predict diseases, assist diagnosis and therapy decisions, and carry out real-time monitoring. This collaboration enables personalized and adaptable clinical decision support while reducing the cognitive load on medical practitioners.

### 1.3 Research Objectives

The primary objectives of this study are:

- To design an Agentic Generative AI framework for smart disease prediction and clinical decision-making.
- To implement autonomous agents and Generative AI to provide explainable and context-aware healthcare support.
- To evaluate the proposed framework and compare its performance with other AI healthcare frameworks.

In light of the increasing integration of Agentic AI, Generative AI, and healthcare analytics, this research presents an Agentic Generative AI Framework for Intelligent Disease Prediction and Decision-Making in Smart Healthcare. The framework unifies prediction, reasoning, explainability, recommendation generation, and monitoring into one integrated system.

## 2. REVIEW OF LITERATURE

Artificial Intelligence has greatly impacted medicine through its ability to predict illnesses, provide medical decision support, and personalize treatment. Machine learning and deep learning methods have helped in diagnosis, patient outcome prediction, and healthcare analytics. However, increasing complexity in clinical settings requires intelligent systems that reason and make decisions autonomously.

### 2.1 Artificial Intelligence and Clinical Decision Support in Healthcare

Early research paved the way for AI-based healthcare systems. Studies on AI in healthcare examined applications in diagnosis, treatment, and healthcare management. Big data and machine learning have been emphasized as important tools for generating clinical insights from healthcare datasets. Deep learning has also contributed to innovation in imaging, diagnostics, and clinical analysis. Clinical Decision Support Systems (CDSS) have shifted from rule-based systems to intelligent platforms, but many remain dependent on predetermined workflows and lack adaptability.

### 2.2 Generative AI and Large Language Models in Healthcare

Generative AI and LLMs have expanded intelligent healthcare applications. Large language models can learn and understand clinical information and perform medical reasoning tasks. GPT-style models have been applied to difficult medical questions, and healthcare-oriented LLMs have shown potential in medical question answering, triage, referrals, and diagnosis. However, reliability, transparency, and clinical deployment remain key challenges.

### 2.3 Explainable AI and Agentic Intelligence in Healthcare

The growing use of AI in medicine increases the need for transparency and explainability. Explainable AI helps clinicians understand how predictions and recommendations are produced. Recent work on Agentic AI focuses on agents that cooperate to accomplish healthcare goals. Agent-based systems can support medical data inference, terminology-aware reasoning, retrieval-augmented recommendations, and autonomous healthcare workflow coordination.

**Table 1.** Comparative summary of existing AI-based healthcare decision support approaches.

| Approach | Strength | Limitation | Research Gap |
|---|---|---|---|
| Traditional CDSS | Rule-based clinical support | Low adaptability | Limited reasoning and learning |
| Machine Learning | Accurate disease prediction | Limited explainability | Weak clinical interpretation |
| Deep Learning | Strong pattern detection | Data intensive and black-box | Limited transparency |
| Generative AI/LLMs | Clinical explanation and text reasoning | Reliability and hallucination risks | Limited workflow integration |
| Agentic AI | Autonomous coordination | Emerging and under-tested | Limited integrated healthcare framework |

According to the literature, there is a clear shift from traditional predictive analytics toward explanatory, generative, and agent-based healthcare intelligence systems. Nevertheless, most current methods focus on individual functions rather than providing a complete healthcare decision support framework.

### 2.4 Identified Research Gaps and Research Motivation

Current AI-powered healthcare systems mainly concentrate on disease prediction and seldom include reasoning, explainability, and adaptive decision-making. Existing LLM-powered healthcare applications often answer queries instead of solving complete clinical problems. Although Agentic AI research is promising, it rarely covers disease prediction, clinical reasoning, treatment recommendation, explainability, and patient monitoring in a single framework.

To overcome these deficiencies, this research introduces an Agentic Generative AI Framework for Intelligent Disease Prediction and Clinical Decision-Making in Smart Healthcare. The framework combines autonomous agents, predictive analytics, Generative AI reasoning, and explainable decision-making in an integrated healthcare environment.

## 3. PROPOSED METHODOLOGY

An Agentic Generative AI Framework is proposed for disease prediction and intelligent decision-making in smart healthcare. Predictive analytics, Generative AI, and intelligent agents form the core components of the framework to facilitate disease prediction, intelligent diagnosis, treatment, and continuous monitoring. Unlike frameworks that focus only on prediction, the proposed framework includes both predictive and reasoning-driven decision-making processes.

The model uses data collected from EHRs, laboratory results, wearable devices, IoMT devices, and medical imaging equipment. Specialized agents cooperate to produce explainable healthcare recommendations.

### 3.1 Architecture of the Proposed Framework

The architecture of the suggested model is shown in Figure 1. It comprises six specialized agents responsible for data collection, data analysis, disease forecasting, medical reasoning, treatment suggestion, and patient monitoring.

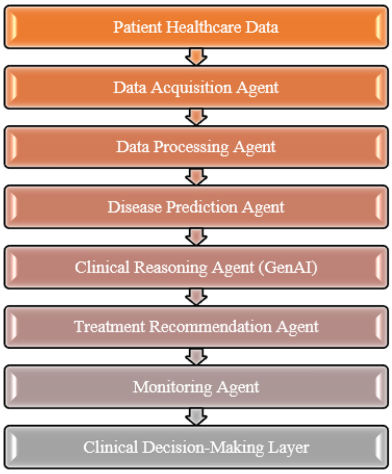


**Figure 1.** Architecture of the proposed Agentic Generative AI Framework for intelligent disease prediction and clinical decision-making.

**Table 2.** Functional roles of intelligent agents in the proposed framework.

| Agent | Primary Function | Generated Output |
|---|---|---|
| Data Acquisition Agent | Collects patient data from EHRs, IoMT devices, laboratory reports, and imaging systems | Integrated healthcare dataset |
| Data Processing Agent | Performs data cleaning, normalization, feature extraction, and validation | Processed patient feature set |
| Disease Prediction Agent | Estimates disease risk using predictive learning models | Disease prediction score |
| Clinical Reasoning Agent | Performs contextual reasoning using Generative AI and medical knowledge resources | Clinical interpretation |
| Treatment Recommendation Agent | Generates personalized treatment strategies | Treatment recommendations |
| Monitoring Agent | Observes patient condition and updates decisions over time | Updated clinical decision support |

### 3.2 Mathematical Formulation

The framework employs patient clinical information as the main input for disease prediction. The patient clinical feature vector is written as:

$$X = \{x_1, x_2, x_3, \ldots, x_n\}. \tag{1}$$

Here, $X$ represents demographic details, physiological measurements, laboratory findings, symptoms, patient history, and sensor-enabled healthcare data.

The Disease Prediction Agent uses the feature vector to calculate the probability of disease occurrence:

$$D_p = f(X), \tag{2}$$

where $D_p$ represents the predicted disease probability and $f(\cdot)$ is the disease prediction model.

The Clinical Reasoning Agent produces contextual interpretations using prediction results, patient context, and medical knowledge sources:

$$CR = g(D_p, K, C), \tag{3}$$

where $CR$ denotes clinical reasoning output, $K$ represents the medical knowledge base, and $C$ denotes patient-specific clinical context.

The Treatment Recommendation Agent develops personalized treatment plans using generated reasoning and patient medical history:

$$TR = h(CR, P_h), \tag{4}$$

where $TR$ represents the treatment recommendation and $P_h$ denotes patient health history.

The Clinical Confidence Score (CCS) measures recommendation reliability:

$$CCS = \frac{N_v}{N_t}, \tag{5}$$

where $N_v$ is the number of clinically validated recommendations and $N_t$ is the total number of generated recommendations.

### 3.3 Proposed Algorithm

**Table 3.** Agentic Generative AI-based disease prediction and clinical decision-making algorithm.

| Algorithm 1 |
|---|
| Input: Patient healthcare data $X$. Output: Disease prediction, clinical explanation, and treatment recommendation. |
| 1. Acquire patient data from EHRs, IoMT devices, laboratory reports, and medical imaging systems. |
| 2. Perform data preprocessing and feature extraction. |
| 3. Generate patient clinical feature vector $X$. |
| 4. Apply disease prediction model to estimate disease probability $D_p$. |
| 5. Retrieve relevant medical knowledge and patient context. |
| 6. Generate clinical reasoning output $CR$ using Generative AI. |
| 7. Produce explainable diagnostic interpretation. |
| 8. Formulate personalized treatment recommendation $TR$. |
| 9. Monitor patient outcomes continuously and update recommendations when new clinical information becomes available. |
| 10. Return disease prediction, clinical reasoning, and treatment recommendation. |

The algorithm facilitates autonomous interaction among specialized agents and supports dynamic healthcare decisions throughout the patient-care process.

### 3.4 Advantages of the Proposed Framework

The proposed framework provides numerous benefits over conventional healthcare intelligence systems:

- Integration of disease prediction, reasoning, and recommendations under a single architecture.
- Independent cooperation among different healthcare agents.
- Generative AI reasoning for explainable decision support.
- Personalized treatment planning and continuous patient monitoring.
- Improved transparency, adaptability, and clinician trust.

## 4. EXPERIMENTAL SETUP AND PERFORMANCE EVALUATION

The proposed Agentic Generative AI framework was evaluated using healthcare datasets and baseline comparison models to determine its performance in disease prediction, clinical reasoning, explainability, and decision-support capability. Both quantitative and qualitative evaluation metrics were used.

### 4.1 Healthcare Datasets

Several publicly accessible healthcare datasets covering different disease categories were considered for testing to establish robustness and generalizability.

**Table 4.** Healthcare datasets used for evaluation.

| Dataset | Disease Category | Features | Records |
|---|---|---|---|
| UCI Heart Disease Dataset | Cardiovascular Disease | 13 | 303 |
| PIMA Indians Diabetes Dataset | Diabetes Mellitus | 8 | 768 |
| Chronic Kidney Disease Dataset | Kidney Disease | 24 | 400 |
| Breast Cancer Wisconsin Dataset | Breast Cancer | 30 | 569 |

These datasets consist of demographic, physiological, laboratory, and diagnostic features, enabling comprehensive validation in various healthcare settings.

### 4.2 Data Preprocessing Strategy

Before training and evaluation, preprocessing was applied to enhance data quality and increase model accuracy. The process included missing data management, duplicate removal, feature normalization, categorical data encoding, feature selection, and dataset splitting into training and testing parts.

### 4.3 Performance Evaluation Metrics

Healthcare classification metrics were used to measure predictive effectiveness. Classification accuracy is:

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}. \tag{6}$$

Precision is:

$$\text{Precision} = \frac{TP}{TP + FP}. \tag{7}$$

Recall is:

$$\text{Recall} = \frac{TP}{TP + FN}. \tag{8}$$

The F1-score is:

$$F1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}. \tag{9}$$

Here, $TP$, $TN$, $FP$, and $FN$ represent true positives, true negatives, false positives, and false negatives. The Clinical Confidence Score in Equation (5) was also used to measure the reliability of AI-generated clinical recommendations.

### 4.4 Comparative Models

The proposed model was benchmarked against representative methods used for predictive analytics in healthcare, including traditional machine learning, deep learning, and Generative AI methods.

**Table 5.** Comparative models used for performance evaluation.

| Model | Category |
|---|---|
| Logistic Regression | Traditional Machine Learning |
| Support Vector Machine | Machine Learning |
| Random Forest | Ensemble Learning |
| Deep Neural Network | Deep Learning |
| LLM-Based Clinical Decision Support System | Generative AI |
| Proposed Agentic Generative AI Framework | Agentic Generative AI |

### 4.5 Qualitative Evaluation Criteria

In addition to prediction accuracy, reasoning ability, interpretability, and adaptability were used to assess intelligent healthcare systems.

**Table 6.** Qualitative evaluation criteria.

| Criterion | Description |
|---|---|
| Explainability | Interpretability of generated recommendations |
| Clinical Reasoning Quality | Context-aware medical reasoning capability |
| Personalization | Adaptation to patient-specific information |
| Adaptability | Dynamic updating of recommendations |
| Decision Support Effectiveness | Clinical usefulness of recommendations |

### 4.6 Experimental Evaluation Workflow

The experimental evaluation workflow is shown in Figure 2. Healthcare data were split into training and testing datasets. The proposed framework was compared with machine learning, deep learning, and AI-assisted decision support approaches using standard performance measures.

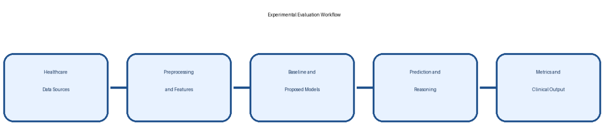


**Figure 2.** Experimental evaluation workflow of the proposed framework.

## 5. RESULTS AND COMPARATIVE EVALUATION

This section evaluates the Agentic Generative AI Framework for disease prediction and clinical decision support. The framework is assessed using predictive accuracy, healthcare intelligence, agent efficacy, computational efficiency, and decision-support reliability.

### 5.1 Comparative Predictive Performance

Predictive efficiency was evaluated using accuracy, precision, recall, and F1-score. Comparative findings are presented in Table 7.

Table 7 shows that the proposed approach outperforms the other approaches in all predictive evaluation measures. The use of autonomous agents and Generative AI-based reasoning improves disease prediction compared with conventional methods and AI-assisted decision support systems.

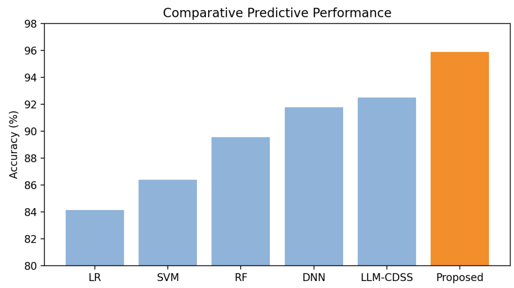


**Figure 3.** Performance improvement of the proposed framework compared with baseline models.

### 5.2 Dataset-Wise Predictive Consistency Analysis

To assess robustness in different healthcare areas, the proposed framework was validated using disease prediction datasets. Dataset-level performance is shown in Table 8.

**Table 8.** Dataset-wise accuracy analysis.

| Dataset | Accuracy (%) |
|---|---|
| UCI Heart Disease | 95.21 |
| PIMA Diabetes | 94.68 |
| Chronic Kidney Disease | 96.42 |
| Breast Cancer Wisconsin | 97.16 |
| Average Accuracy | 95.87 |

The outcomes show consistent predictive accuracy across different healthcare datasets. The proposed method demonstrates flexibility when applied to various healthcare environments.

**Table 7.** Comparative predictive performance of evaluated models.

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1 (%) |
|---|---|---|---|---|
| Logistic Regression | 84.12 | 82.75 | 83.46 | 83.10 |
| Support Vector Machine | 86.38 | 85.72 | 85.91 | 85.81 |
| Random Forest | 89.54 | 88.93 | 89.11 | 89.02 |
| Deep Neural Network | 91.76 | 91.04 | 90.82 | 90.93 |
| LLM-Based Clinical Decision Support | 92.48 | 91.83 | 91.65 | 91.74 |
| Proposed Agentic Generative AI Framework | 95.87 | 95.14 | 94.92 | 95.03 |

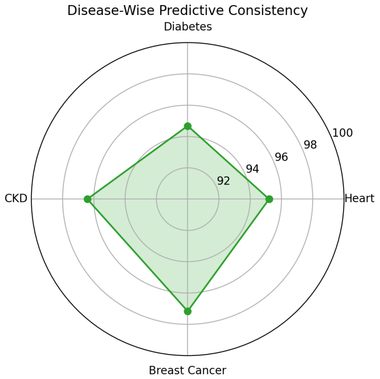


**Figure 4.** Disease-wise predictive consistency across healthcare datasets.

### 5.3 Agent-Level Operational Analysis

In the proposed architecture, intelligent agents work collaboratively for healthcare decision-making. Their roles were analyzed using operational contribution analysis.

**Table 9.** Agent-level contribution to clinical decision support.

| Agent | Contribution Score (%) |
|---|---|
| Data Acquisition Agent | 12 |
| Data Processing Agent | 16 |
| Disease Prediction Agent | 27 |
| Clinical Reasoning Agent | 24 |
| Treatment Recommendation Agent | 13 |
| Monitoring Agent | 8 |

The Disease Prediction Agent and Clinical Reasoning Agent are the major contributors to decision-support performance.

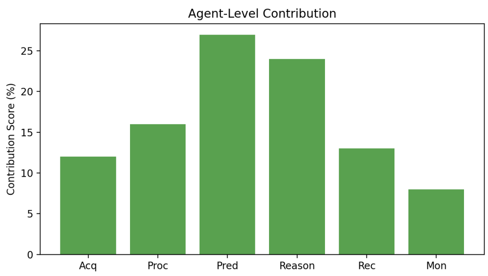


**Figure 5.** Inter-agent communication frequency within the proposed Agentic Generative AI Framework.

### 5.4 Clinical Confidence and Recommendation Reliability

Healthcare systems must provide recommendations that can be trusted to have clinical significance. The Clinical Confidence Score was used to evaluate recommendation quality.

**Table 10.** Clinical recommendation reliability assessment.

| Evaluation Criterion | Score (%) |
|---|---|
| Recommendation Validity | 94.6 |
| Contextual Relevance | 95.1 |
| Consistency | 93.8 |
| Clinical Confidence Score | 94.5 |

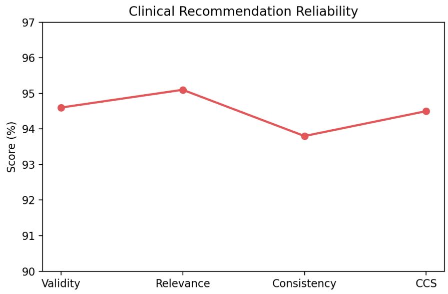


**Figure 6.** Clinical recommendation reliability assessment.

### 5.5 Healthcare Intelligence Capability Assessment

In addition to accurate predictions, intelligent healthcare systems should support explanations, personalization, adaptability, and reasoning.

The proposed framework offers higher healthcare intelligence capability because it combines autonomous reasoning, explainable prediction, and adaptive recommendation generation.

### 5.6 Computational and Clinical Effectiveness

The proposed framework was also evaluated in terms of execution time, response quality, and clinical usefulness. Although the integration of multiple agents introduces additional processing overhead, the framework provides better interpretability, stable recommendation quality, and improved decision-support effectiveness compared with isolated prediction models.

## 6. DISCUSSION

The results indicate that the proposed Agentic Generative AI Framework achieves strong predictive performance and improved clinical decision-support capability. The combination of predictive analytics and Generative AI reasoning enables the system to move beyond isolated classification and toward context-aware healthcare intelligence.

**Table 11.** Comparative healthcare intelligence assessment.

| Model | Explainability | Reasoning | Personalization | Adaptability |
|---|---|---|---|---|
| Traditional ML | Low | Low | Medium | Low |
| Deep Learning | Low | Medium | Medium | Low |
| LLM-Based CDSS | Medium | High | Medium | Medium |
| Proposed Framework | High | High | High | High |

### 6.1 Predictive and Reasoning Advantages

The proposed model outperforms traditional machine learning, deep learning, and LLM-based clinical decision support models. This performance improvement can be attributed to the interaction among specialized agents and the integration of patient context, disease probability, medical knowledge, and treatment recommendation logic. Unlike conventional models, the framework produces both prediction scores and clinical interpretations.

### 6.2 Comparison with Existing Approaches

Conventional machine learning techniques can make accurate predictions but often lack reasoning, explainability, and decision-support mechanisms. Healthcare applications using LLMs can enhance reasoning and recommendations but tend to remain separate advisory tools without integrated workflow management or coordination across healthcare systems.

The proposed framework differentiates itself by combining disease prediction, medical reasoning, recommendation generation, monitoring, and agent collaboration in one system. Earlier research has concentrated on predictive applications, explainable medical AI, or LLM-based clinical reasoning. The suggested framework combines these aspects into a comprehensive decision-support system.

### 6.3 Role of Agentic Intelligence in Clinical Decision Support

The findings illustrate the significance of cooperative autonomous agents in healthcare settings. Dedicated agents perform complementary roles and share information continuously during the clinical process. This cooperation allows recommendations to be generated from predictive intelligence and contextual reasoning, making healthcare decisions more transparent and personalized.

### 6.4 Implications for Smart Healthcare

The proposed framework has practical potential in smart hospitals, telemedicine services, IoMT-based monitoring frameworks, and clinical decision support systems. Through predictive analytics and reasoning, the framework can help healthcare practitioners analyze patient information, determine clinical priorities, and plan personalized treatment. Explainable reasoning can also increase clinician confidence in AI-generated recommendations.

### 6.5 Limitations and Future Research Directions

Despite its positive qualities, the study has limitations. First, the experiment is based on open-source healthcare datasets and may not fully reflect real clinical environments. Second, practical implementation requires careful consideration of privacy, interoperability, security, and clinical governance.

Future research could address real-world validation, federated learning for privacy preservation, integration of multimodal healthcare data, retrieval-augmented medical knowledge systems, and improved coordination mechanisms among adaptive agents. Further testing across additional disease domains may refine intelligent healthcare decision-support frameworks.

## 7. CONCLUSION AND RECOMMENDATIONS

This study proposed the Agentic Generative AI Framework for Intelligent Disease Prediction and Clinical Decision-Making in Smart Healthcare. The framework uses predictive analytics, Generative AI-enabled reasoning, and autonomous intelligent agents in a coherent system to support disease prediction, clinical decision-making, therapy suggestion, and patient monitoring.

The framework addresses weaknesses in current healthcare intelligence solutions by integrating prediction, explainability, contextual reasoning, personalization, and adaptive decision-making. Experimental analysis demonstrated predictive accuracy, recommendation reliability, consistency across healthcare datasets, and improved healthcare intelligence compared with traditional ML, DL, and LLM-based systems.

The integration of Agentic AI and Generative AI can greatly enhance healthcare decision-making effectiveness and flexibility. Collaboration among autonomous agents can form an intelligent, patient-focused healthcare ecosystem capable of handling complex clinical scenarios.

Based on the results, the following recommendations are proposed:

- Validate the model using real clinical data.
- Include multimodal healthcare data from sensors, imaging, and EHRs.
- Add security components using privacy preservation and federated learning.
- Enable clinician-oriented reasoning through retrieval-augmented medical knowledge.
- Implement efficient coordination mechanisms for multi-agent systems.
- Test the model across additional healthcare disease domains.

## REFERENCES

[1] Singhal, K., Azizi, S., Tu, T., Mahdavi, S. S., Wei, J., Chung, H. W., et al. (2023). Large language models encode clinical knowledge. *Nature*, 620(7972), 172–180.

[2] Singhal, K., Tu, T., Gottweis, J., Sayres, R., Wulczyn, E., Amin, M., et al. (2025). Toward expert-level medical question answering with large language models. *Nature Medicine*, 31(3), 943–950.

[3] Maity, S., and Saikia, M. J. (2025). Large language models in healthcare and medical applications: a review. *Bioengineering*, 12(6), 631.

[4] Scott, I. A., Reddy, S., Kelly, T., Miller, T., and Van Der Vegt, A. (2025). Using generative artificial intelligence in clinical practice: a narrative review and proposed agenda for implementation. *Medical Journal of Australia*, 223(11), 664–672.

[5] Rabbani, S. A., El-Tanani, M., Sharma, S., Rabbani, S. S., El-Tanani, Y., Kumar, R., and Saini, M. (2025). Generative artificial intelligence in healthcare: applications, implementation challenges, and future directions. *BioMedInformatics*, 5(3), 37.

[6] Gaber, F., Shaik, M., Allega, F., Bilecz, A. J., Busch, F., Goon, K., et al. (2025). Evaluating large language model workflows in clinical decision support for triage, referral, and diagnosis. *NPJ Digital Medicine*, 8(1), 263.

[7] Topol, E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56.

[8] Esteva, A., Robicquet, A., Ramsundar, B., Kuleshov, V., DePristo, M., Chou, K., et al. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25(1), 24–29.

[9] Rajpurkar, P., Chen, E., Banerjee, O., and Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, 28(1), 31–38.

[10] Beam, A. L., and Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA*, 319(13), 1317–1318.

[11] Miotto, R., Wang, F., Wang, S., Jiang, X., and Dudley, J. T. (2018). Deep learning for healthcare: review, opportunities and challenges. *Briefings in Bioinformatics*, 19(6), 1236–1246.

[12] Jiang, F., Jiang, Y., Zhi, H., Dong, Y., Li, H., Ma, S., et al. (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and Vascular Neurology*, 2(4).

[13] Yu, K. H., Beam, A. L., and Kohane, I. S. (2018). Artificial intelligence in healthcare. *Nature Biomedical Engineering*, 2(10), 719–731.

[14] Shortliffe, E. H., and Sepúlveda, M. J. (2018). Clinical decision support in the era of artificial intelligence. *JAMA*, 320(21), 2199–2200.

[15] Sutton, R. T., Pincock, D., Baumgart, D. C., Sadowski, D. C., Fedorak, R. N., and Kroeker, K. I. (2020). An overview of clinical decision support systems: benefits, risks, and strategies for success. *NPJ Digital Medicine*, 3(1), 17.

[16] Holzinger, A., Langs, G., Denk, H., Zatloukal, K., and Müller, H. (2019). Causability and explainability of artificial intelligence in medicine. *WIREs Data Mining and Knowledge Discovery*, 9(4), e1312.

[17] Samek, W., Montavon, G., Vedaldi, A., Hansen, L. K., and Müller, K. R. (Eds.). (2019). *Explainable AI: Interpreting, Explaining and Visualizing Deep Learning*. Springer Nature.

[18] Helen, D., and Suresh, N. V. (2024). Generative AI in healthcare: opportunities, challenges, and future perspectives. In *Revolutionizing the Healthcare Sector with AI* (pp. 79–90).

[19] Nori, H., King, N., McKinney, S. M., Carignan, S., and Horvitz, E. (2023). Capabilities of GPT-4 on medical challenge problems. *arXiv preprint*, arXiv:2303.13375.

[20] Chen, Y., Huang, D., Shen, Y., Xu, H., Sheng, L., Zhou, Q., and Wang, K. (2025). MedCT: a clinical terminology graph for generative AI applications in healthcare. In *International Conference on Computational Science* (pp. 24–38). Cham: Springer Nature Switzerland.

[21] Shimgekar, S. R., Vassef, S., Goyal, A., Saha, K., Zonooz, P., and Kumar, N. (2025). Agentic AI framework for end-to-end medical data inference. In *2025 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)* (pp. 7807–7810). IEEE.

[22] Srinivasu, P. N., Aruna Kumari, G. L., Ahmed, S., and Alhumam, A. (2026). Exploring agentic AI in healthcare: a study on its working mechanism. *Frontiers in Medicine*, 12, 1753443.

[23] Zhao, L., Liu, S., Xin, T., Tan, J., Wang, X., Li, Y., et al. (2026). AI agent in healthcare: applications, evaluations, and future directions. *NPJ Artificial Intelligence*, 2(1), 31.

[24] Liu, Y., Carrero, Z. I., Jiang, X., Ferber, D., Wölflein, G., Zhang, L., et al. (2026). Benchmarking large language model-based agent systems for clinical decision tasks. *NPJ Digital Medicine*.

[25] Garza, L., Kotal, A., Grasso, M. A., and Umucu, E. (2025). Retrieval-Augmented Framework for LLM-Based Clinical Decision Support. *arXiv preprint*, arXiv:2510.01363.

[26] Sidhu, R. S., Farwaha, H. S., Kumar, R., Bains, P. S., Prakash, C., Kumar, R., Chowdhury, S., and Chan, C. K. (2024). Comparative study of metallic foil friction stir welded and conventional friction stir welded AZ61 Mg alloy butt joints: biomedical and engineering applications. *AIP Advances*, 14(4), 045209.

[27] Alolayyan, M. N., et al. (2025). The mediating role of medical service geographical availability between healthcare service quality and medical insurance. In A. Hannoon and A. Mahmood (Eds.), *Intelligence-Driven Circular Economy* (Studies in Computational Intelligence, Vol. 1174). Cham: Springer.

[28] Mohammad, A. A. S., et al. (2026). Medical power electronics: innovations, applications, and challenges. In M. Alsyasneh and J. Masih (Eds.), *Artificial Intelligence for Agile Business Solutions* (Studies in Systems, Decision and Control, Vol. 633). Cham: Springer.

[29] Praveen, S. P., Hasan, M. K., Abdullah, S. N. H. S., Sirisha, U., Tirumanadham, N. S. K. M. K., Islam, S., et al. (2024). Enhanced feature selection and ensemble learning for cardiovascular disease prediction: hybrid GOL2-2T and adaptive boosted decision fusion with babysitting refinement. *Frontiers in Medicine*, 11, 1407376.

[30] Praveen, S. P., Sandeep, K., Sai, N. R., Sharma, A., Pandey, J., and Chouhan, V. (2024). Outlier management and its impact on diabetes prediction: a voting ensemble study. *Journal of Intelligent Systems and Internet of Things*, 12(1), 08–19.

[31] Praveen, S. P., Ghasempoor, H., Shahabi, N., and Izanloo, F. (2023). A hybrid gravitational emulation local search-based algorithm for task scheduling in cloud computing. *Mathematical Problems in Engineering*, 2023, 6516482.

[32] Praveen, S. P., Sidharth, S. R., Priya, T. K., Kavuri, Y. S., Sindhura, S. M., and Donepudi, S. (2023). ResNet and ResNeXt-powered kidney tumor detection: a robust approach on a subset of the KAUH dataset. In *2023 2nd International Conference on Automation, Computing and Renewable Systems (ICACRS)* (pp. 749–757). IEEE.

[33] Chowdary, N. S., Kadiyala, S., Jyothi, V. E., Srinandan, P., Praveen, S. P., and Prakash, P. B. (2025). Identity and proxy orientation based remote data integration checking and uploading in public clouds. In *2025 3rd International Conference on Communication, Security, and Artificial Intelligence (ICCSAI)* (pp. 1–5). IEEE.