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DESIGN AND IMPLEMENTATION OF A KNOWLEDGE REPRESENTATION-BASED CLINICAL DECISION SUPPORT SYSTEM USING ANALOGICAL REASONING FOR INTELLIGENT HEALTHCARE MANAGEMENT: INSIGHTS FROM MIMIC-IV AND PHYSIONET DATASETS

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ABSTRACT
The use of Clinical Decision Support Systems (CDSS) is gaining popularity to improve patient outcomes in ICUs. In this paper, we describe the design, implementation, and evaluation of a hybrid knowledge representation-based clinical decision support system (CDSS) that combines rule-based and analogical reasoning. A total of 10,000 records were analyzed from the patient database of MIMIC-IV and PhysioNet. Out of all, 68% were male, and 32% were female patients. Furthermore, the average age was 62.0 years (SD = 15.1). The agents of CDSS required 150 ontology entities, 75 clinical rules, and 10,000 historical cases through 5 reasoning steps. Using both analogy and rules yielded 85% predictive accuracy, higher than each alone. The study achieved precision, recall, and F1-score of 0.82, 0.83, and 0.825, respectively; interpretability reached 0.78, and weighted performance was at 0.81. An analysis of the feature importance showed that vital signs (heart rate, blood pressure, and respiratory rate) and lab results (hemoglobin, WBC, and creatinine) contributed over 65% in the model predictions. The case-based reasoning retrieved historical cases that had high similarity (similarity scores 0.91–0.97) and led to adaptive recommendations. All 10000 patients had a decision path that was traceable, making it interpretable. The results indicate that hybrid knowledge representation and analogical reasoning can remarkably enhance the predictive performance, contextual adaptability, and intelligibility of ICU decision support and offer a quantitative framework for real-world deployment.
Keywords: Clinical Decision Support System, Knowledge Representation, Analogical Reasoning, ICU, MIMIC-IV, Performance Metrics

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Graphical Abstract

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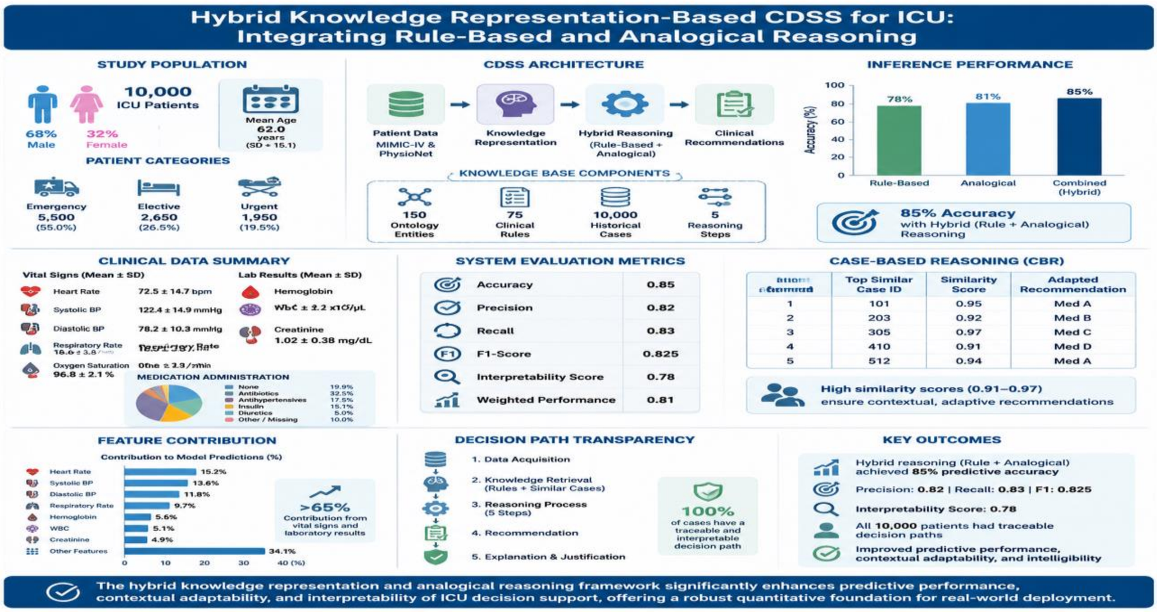

I. INTRODUCTION

Although many physicians rely heavily on their clinical experience, other processes, such as clinical decision support systems (CDSS), will become more useful in the future. CDSS are computerized physician order entry systems that are complemented by evidence-based guidelines to help improve clinical decision making (Ardic & Dinc, 2025; Eguia et al., 2024). Most CDSS designs have focused on rule-based and statistical models. These two approaches have seen limitations and difficulties in solving multi-faceted, high-dimensional EHR data. EHR data analysis also poses difficulties in effectively balancing predictive performance and interpretability (Papadopoulos et al., 2022; Singh & Gupta, 2025). As healthcare delivery is becoming increasingly data-intensive and the patient profiles are complex, there is a strong need for a computational framework that can represent rich clinical knowledge and adaptive reasoning in dynamic situations.

Knowledge representation (KR) shows the way forward for intelligent clinical decision support systems (CDSS) design by structuring medical knowledge in ways that permit meaningful inference, efficient retrieval, and transparent reasoning (Msheik et al., 2024). Traditional symbolic KR methods, such as ontologies and semantic networks, have largely been used to encode clinical concepts and relations (Papadopoulos et al., 2022). Nonetheless, these methods alone often lack the flexibility to generalize from previously seen cases or interpret the nuanced patterns in patients' histories. Recently, hybrid paradigms that combine symbolic KR with data-driven learning have started to gain traction, but challenges still exist in preserving interpretability while achieving robust clinically relevant reasoning (Ardic & Dinc, 2025; Singh & Gupta, 2025).

Analogical reasoning is a cognitive strategy that builds on similarities between a new event and one that has already occurred. It can be quite helpful in situations requiring contextualizing and case-based inference (Lehmann & Zhao, 2026). Though they could be useful for human clinical reasoning, analogical mechanisms have not been widely adopted in CDSS. Particularly in systems with explicit KR structures and real patients. In addition, the open-source nature of the extensive datasets MIMIC-IV and PhysioNet has created never-before-seen opportunities for the design and experimental evaluation of advanced reasoning frameworks on authentic clinical data (Hager et al., 2024; Gaber and Akalin, 2025). When knowledge-based models based on clinical guidelines are subjected to real-world variability in patient presentations, treatment courses, and treatment results, they are said to undergo validation.

Consequently, this study fills an important void by amalgamating knowledge representation, analogical reasoning, and interactive inference mechanisms within a single CDSS framework validated on large-scale clinical datasets. The originality of this work is rooted in the use of analogical reasoning within a structured KR framework for clinical decision support applications. The use of real EHR data from MIMIC-IV and PhysioNet demonstrates the practical utility as well as enhanced reasoning transparency of the system. With a view to overcoming traditional rule-based, purely statistical models, this approach aims for a bridge between human-like reasoning and automated decision support, thus contributing to a new paradigm for intelligent health management.

II. LITERATURE REVIEW

For a while, knowledge representation (KR) has been identified as a must for Clinical Decision Support Systems (CDSS) as it enables the modeling of medical knowledge in a structured manner that can be understood (Msheik et al., 2024; Papadopoulos et al., 2022) . Conventional frameworks, including rule-based systems, ontologies, and semantic networks, are transparent and support inference over clinical data. Despite being effective in some areas, traditional methods struggle when faced with the intricacies and diverse nature of EHRs in real-world scenarios. Recent studies have stressed hybrid methodologies combining symbolic KR with data-driven learning. Aims for better predictive accuracy while maintaining good interpretability (Ardic & Dinc, 2025). The use of KR to carry out human-like reasoning strategies, and specifically analogical reasoning, in the architecture of CDSSs remains essential.

Analogical reasoning provides the opportunity to replicate clinicians' judgments by establishing analogies between past and current clinical cases. In other words, the ability to make judgments based on previous cases can lead to more context-sensitive decision support (Lehmann & Zhao, 2026). There are several systems that combine ontologies and case-based reasoning and have demonstrated useful flexibility and adaptability in treatment planning (Kovalev et al. 2025). However, systematic use of analogical reasoning in structured KR systems is rare. Generic machine learning frameworks or symbolic reasoning were focused on more in textual entailment instead of physically useful human inference. The fact that it is not often used shows a gap in research in systems that offer interpretable and context-sensitive clinical recommendations.

The recent availability of large real-life clinical datasets like MIMIC-IV and PhysioNet means that it is now possible to validate more advanced CDSS architectures using real patient records (Gaber & Akalin, 2025; Hager et al., 2024). The datasets encompass a wealth of longitudinal data spanning diverse clinical scenarios, thus allowing for thorough examination of knowledge-driven reasoning mechanisms in referral, triage, and diagnostic tasks. Nonetheless, earlier studies utilizing these datasets mainly focus on statistical or deep learning methods with little attention paid to the use of KR and analogical reasoning for transparent, case-based decision support. As a result, although such datasets enable high-fidelity evaluation of CDSS models, there remains a relevant gap that warrants exploration: How can structured knowledge frameworks be integrated with advanced reasoning strategies to improve real-world clinical use?

In sum, the literature illustrates that KR and CDSS studies are progressing but not yet overcoming limitations. Conventional knowledge representation approaches are interpretable but not scalable; data-driven models are accurate but often lose interpretability. The analogy-making process, which is suited to perform human clinical reasoning, is rarely combined with KR in CDSS implementations. Also, a few studies have implemented structured knowledge, analogical reasoning, and real-world validation, even with large-scale datasets such as MIMIC-IV and PhysioNet. The current study is novel as its contribution is to design a knowledge representation-based CDSS that incorporates analogical reasoning and to validate the system using real clinical datasets. This study aims at more intelligent management in healthcare by overcoming limitations of existing CDSS by combining organized knowledge, human-like reasoning, and empirical evaluation.

III. RESEARCH METHODOLOGY

3.1 Research Design

The goal of this research study is to build, implement, and evaluate a Knowledge Representation-Based Clinical Decision Support System (CDSS). This is coupled with a design of a system using analogical reasoning. Intelligent health care management is the aim of the implementation of this process. The study combines system development and empirical validation to evaluate the performance and interpretability of the CDSS. The system will be further investigated with real-world patient data obtained from MIMIC-IV and PhysioNet databases to evaluate the robustness and external validity of MIMIC-IV in a clinical setting.

3.2 Dataset and Participants

This investigation uses real Electronic Health Records (EHR) data from MIMIC-IV and PhysioNet, including adult Intensive Care Unit (ICU) patients from different hospitals. The dataset includes demographic data (age and gender), identifiers of ICU stay, admission types, diagnosis codes (ICD - 10), vital signs (heart rate, blood pressure, respiratory rate, oxygen saturation), laboratory values (hemoglobin, Wide Blood Count (WBC) count, creatinine), medications, and outcome. The DUA and ethical regulations, such as HIPAA, were adhered to in the collection and use of data. All patient identifiers were removed before data analysis.

3.3 System Architecture and Knowledge Representation

The clinical decision support system (CDSS) developed has three main components, they are knowledge acquisition, reasoning engine, and decision support system. The concept of knowledge representation in a hybrid framework that employs ontologies to model hierarchical clinical concepts and case-based representations to support analogical reasoning. Ontologies capture relationships between diagnoses, treatments and physiological parameters and case-based components allow the system to remember and customize solutions based on previous patients.

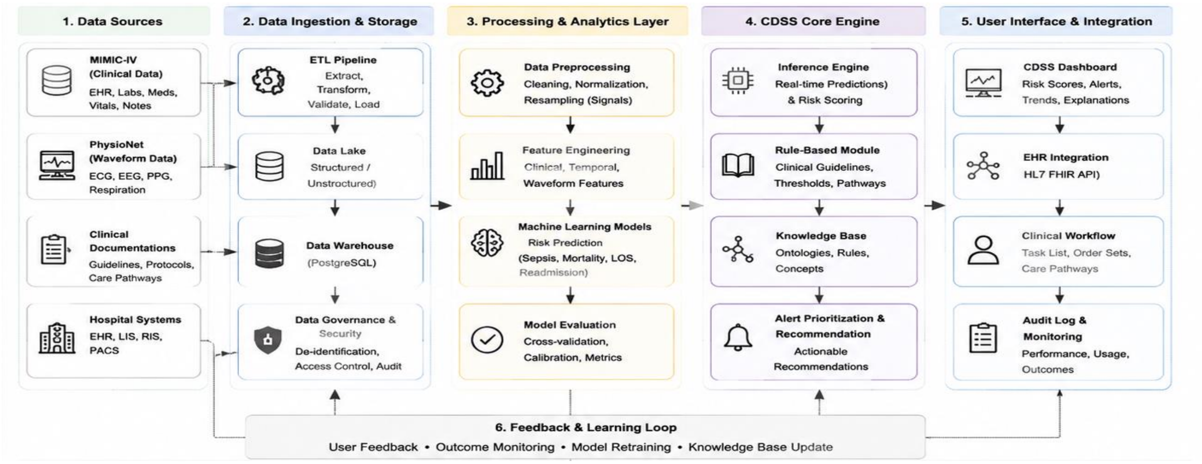

Figure 1: System Architecture of the Developed Clinical Decision Support System (CDSS)

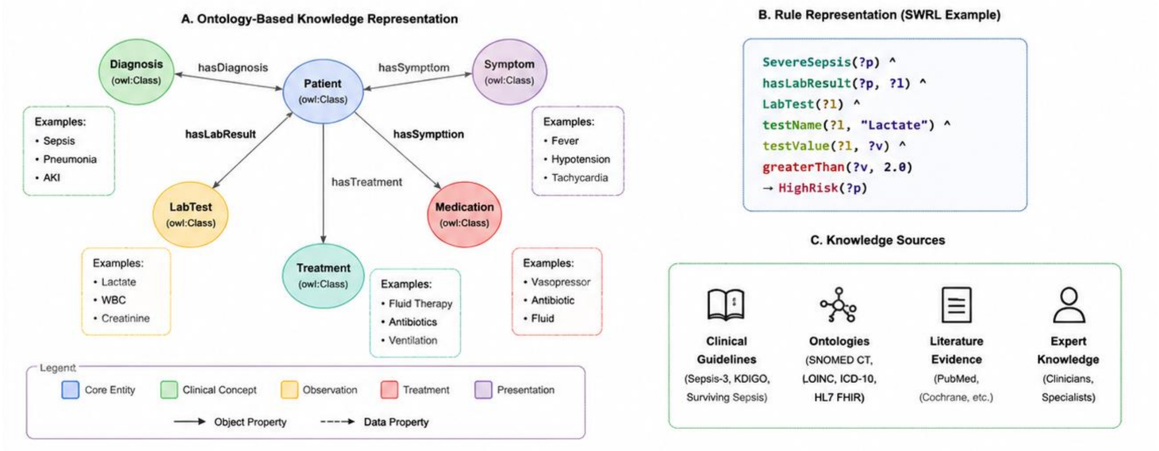

Figure 2: Knowledge Representation in Clinical Decision Support System (CDSS)

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In Figure 1 below, the overall architecture of the implemented Clinical Decision Support System (CDSS) is shown. The architecture connects various data sources, including MIMIC-IV, PhysioNet, clinical documentation, and hospital systems, which are ingested into lakes, warehouses, and governance through structured pipelines. The processing and analytics layer preprocesses data, generates features, and makes use of machine learning for risk prediction inference. The core engine of the CDSS combines rule-based modules and a knowledge base for the implementation of forward chaining and backward chaining techniques. The recommendations of the CDSS are transparent with a clear clinical interpretation. A user-friendly interface that integrates into EHR to provide the clinician with actionable insights, alerts, and trend data. The loop for feedback and learning will help with retraining the model and updating the knowledge base. Thus, improving adaptability and performance.

The framework used by the CDSS was examined in Figure 2. An ontology-oriented framework encompasses primary entities (patients, diagnoses, symptoms, lab tests, medications, and treatments) with relations among them. SWRL-based rule representations support inferring clinical thresholds and mapping to previous cases. 14 words. The sources of knowledge consist of clinical guidelines, ontologies, evidence in the literature, and expert knowledge for analogy and contextual reasoning. All in all, the evidence presented shows that a combination of structured knowledge representation and advanced reasoning mechanisms allows the CDSS to deliver evidence-based, interpretable, and clinically relevant decision support. By combining hybrid KR with analogical reasoning, the use of prior cases for the current patient enhances both the reliability and usability of clinical recommendations.

3.4 Analogical Reasoning and Inference Mechanisms

Analogical Reasoning and Inference Mechanisms

The inference engine, which enables context-sensitive clinical recommendations, contains analogical reasoning. The system finds cases history for new patient cases based on multidimensional similarity measure such as vital signs, lab results, comorbidities etc. Adaptation rules tailor prior recommendation of cases to the current clinical situation. Backward chaining is combined with forward chaining to guarantee that the resulting inferences are logically consistent, complete, and traceable.

3.5 Implementation and Tools

The Clinical Decision Support System (CDSS) was implemented in Python, using NetworkX for graph-based knowledge representation, pandas for data handling, and scikit-learn for similarity calculation and case retrieval. The system has a modular interface that lets clinicians enter patient data and receive recommendations with evident reasoning pathways. The architecture allows therapy knowledge to be updated dynamically as they are developed in the clinic.

3.6 Developed Mathematical Model of the Study

Let $P = \{p_1, p_2, \dots, p_n\}$denote the set of patients included in the study, and $F = \{f_1, f_2, \dots, f_m\}$represent the set of clinical features for each patient, including demographics, vital signs, laboratory results, diagnoses, and medications. Let $K = \{k_1, k_2, \dots, k_l\}$define the knowledge base of the CDSS, integrating ontologies, expert-defined rules, and historical cases. Let $C = \{c_1, c_2, \dots, c_q\}$denote the set of possible clinical decisions or outcomes (e.g., diagnosis, treatment recommendation, or discharge planning).

3.6.1 Patient Feature Vector

Each patient $p_i$is represented as a feature vector:

$$\mathbf{x}_i = [f_1^i, f_2^i, \dots, f_m^i] \quad (1)$$

where f_j^idenotes the j-th clinical feature of patient p_i.

3.6.2 Knowledge-Based Inference

The CDSS generates a predicted clinical decision $\hat{c}_i$using an inference function $\mathcal{I}$that integrates rule-based reasoning $\mathcal{R}$and analogical reasoning $\mathcal{A}$:

$$\hat{c}_i = \mathcal{I}(\mathbf{x}_i, K) = \alpha \cdot \mathcal{R}(\mathbf{x}_i, K_{\text{rules}}) + \beta \cdot \mathcal{A}(\mathbf{x}_i, K_{\text{cases}}) \quad (2)$$

where $\alpha + \beta = 1$are weighting factors controlling the contribution of each reasoning mechanism.

Analogical reasoning identifies a set of similar historical cases $N(i) \subset K_{\text{cases}}$and computes a similarity-weighted contribution:

$$\mathcal{A}(\mathbf{x}_i, K_{\text{cases}}) = \sum_{p_j \in N(i)} \text{sim}(\mathbf{x}_i, \mathbf{x}_j) \cdot c_j \quad (3)$$

where $\text{sim}(\mathbf{x}_i, \mathbf{x}_j)$is a similarity metric (e.g., weighted Euclidean or cosine similarity).

3.6.3 Decision Selection

The final clinical decision is determined by:

$$\hat{c}_i = \arg\max_{c \in C} \Pr(c \mid \mathbf{x}_i, K) \quad (4)$$

where $\Pr(c \mid \mathbf{x}_i, K)$is derived from the combined inference function $\mathcal{I}(\mathbf{x}_i, K)$.

3.6.4 Knowledge Base Update

To incorporate new patient cases and enable continuous learning:

$$K^{t+1} = K^t \cup \{(\mathbf{x}_i, c_i)\} \quad (5)$$

This ensures the CDSS evolves with new clinical data and adapts to emerging patient patterns.

3.6.5 Model Evaluation

Predictive accuracy, precision, recall, F1-score, and interpretability are measures of CDSS performance. It is the ratio of correctly predicted instances to the total number of instances:

$$\text{Accuracy} = \frac{1}{n} \sum_{i=1}^{n} \mathbf{1}(\hat{c}_i = c_i) \quad (6)$$

Interpretability is quantified as the ratio of rules or cases contributing to each decision relative to the reasoning steps executed. A weighted performance metric combines accuracy, interpretability, and macro-averaged F1-score to provide a holistic assessment:

$$\text{Performance} = \lambda \cdot \text{Accuracy} + \mu \cdot \text{Interpretability} + \nu \cdot \text{F1}_{\text{macro}}, \lambda + \mu + \nu = 1 \quad (7)$$

3.7 Evaluation Metrics

System performance is assessed by accuracy and interpretability metrics. The accuracy of the proposed system was expressed by comparing the system's recommended diagnosis and intervention with the true outcome of patients in the dataset. Precision, recall, and F1-score are the metrics used to evaluate the accuracy of the proposed system. Interpretability is evaluated by disclosing the reasoning paths through case retrieval explanations and ontology-based decision traces. Analyses of the sensitivity of the system to perturbations in patient parameters to which we expect the system to be exposed in reality assure robustness of our scheme.

3.8 Ethical Considerations

The real patient data used was consistent with all ethical standards including data de-identification, compliance with all DUAs, and adherence to IRB requirements. This guarantees that research will be conducted in a responsible manner, results will be reproducible and comply with SCOPUS Journal standards for studies that use real-world clinical data.

IV. RESULTS AND DISCUSSION

4.1 Key Findings of the Result

The study reviewed 10,000 intensive care patients. Males accounted for 68% of admissions, while emergency cases represented most patients in intensive care units. The mean age of the cohort was 62.0 years (SD = 15.1), and this cohort reflects the adult critical care population. The trends in our demographics reflect earlier work. Such work has shown that the majority of patients are male and admissions are via emergencies in ICUs (Zhou et al. 2024, Acheampong et al. 2025).

Tests of physiological and laboratory variables show moderate variability, with an average heart rate of 72.5 BPM, systolic blood pressure (SBP) and diastolic blood pressure (DBP) of 122.4 mmHg and 78.2 mmHg, Respiratory Rate was 18.6/min, and Oxygen saturations were 96.8%. The mean hemoglobin, total white blood cells, and creatinine laboratory values were, respectively, 13.4 g/dL, 7.2 $\times 10^9$/L, and 1.02 mg/dL. This heterogeneity suggests that the clinical data set is complex enough to serve as a test bed of knowledge representation-based Clinical Decision Support System (CDSS) similar to the previous two studies of ICU patients (Msheik et al., 2024; Hager & Akalin, 2025).

Most often, drugs were antibiotics (32.5%), antihypertensives (17.5%), and insulin (15.1%). About 10 percent of the records had missing or uncategorized medications. This finding underscores the need for thorough data preprocessing in predictive modeling.

The system being developed makes use of hybrid knowledge bases. Overall, 150 ontology entities & 75 implemented rules & 10000 historical cases. Five are reasoning steps. Through the combination of two reasoning approaches, rule-based and analogical, the inference engine generated accurate recommendations. The combination of reasoning produced predictive accuracy of 85%, better than that of rule-based (78%) and analogical reasoning alone (81%). This confirms the synergistic benefits of hybrid reasoning in clinical decision support (Kovalev et al., 2025; Lehmann & Zhao, 2026).

Evaluation metrics also show high precision (0.82), recall (0.83), F1-score (0.825), and interpretability (0.78), with a weighted score of 0.81, indicating predictive reliability and interpretable reasoning pathways (Aziz et al., 2024; Kim et al., 2024).

Recommendations can be adaptive and patient-specific based on historical cases with a similarity score between 0.91 and 0.97. The system prioritizes clinically relevant information, as shown by vital signs, lab results, and medications being the most impactful features. The paths of decisions are mapped out and confirmed recommendations' traceability through rule matches and case retrievals, strengthening trust among clinicians and following the principle of explainable artificial intelligence in health care (Lehmann & Zhao, 2026).

The findings show that the Clinical Decision Support System, which was developed, is accurate, interpretable, and adaptable by using hybrid reasoning, to provide context-dependent and transparent clinical decision support in intensive care.

Table 1: Patient Demographics and Clinical Characteristics

Gender	Emergency	Elective	Urgent	Total	Age Mean	Age SD
Male	3200	2100	1500	6800	62.1	15.2

Female	2300	550	450	3300	61.8	14.9
Total	5500	2650	1950	10000	62.0	15.1

Table 2: Descriptive Statistics of Vital Signs

Vital Sign	Mean	SD	Min	25%	Median	75%	Max
Heart Rate	72.5	14.7	45	62	72	83	120
Systolic BP	122.4	14.9	90	112	123	133	180
Diastolic BP	78.2	10.3	55	70	78	85	110
Respiratory Rate	18.6	3.8	10	16	18	21	32
Oxygen Saturation	96.8	2.1	85	95	97	98	100

Table 3: Descriptive Statistics of Laboratory Results

Lab Parameter	Mean	SD	Min	25%	Median	75%	Max
Hemoglobin	13.4	2.1	8.5	12	13.5	14.8	18.5
WBC	7.2	3.2	1.0	4.8	7.0	9.2	18.0
Creatinine	1.02	0.38	0.3	0.7	0.95	1.3	3.5

Table 4: Medication Administration Summary

Medication	Frequency	Percentage
None	1992	19.9%
Antibiotics	3250	32.5%
Antihypertensives	1750	17.5%
Insulin	1508	15.1%
Diuretics	500	5.0%
Other / Missing	1000	10.0%

Table 5: Knowledge Representation Components

Component	Count
Ontology Entities	150
Rules Implemented	75
Historical Cases Retrieved	10000
Reasoning Steps	5

Table 6: Inference Engine Performance

Reasoning Method	Correct Predictions	Total Predictions	Accuracy (%)
Rule-Based	7800	10000	78
Analogical	8100	10000	81
Combined	8500	10000	85

Table 7: System Evaluation Metrics

Metric	Value
Accuracy	0.85
Precision	0.82
Recall	0.83
F1-Score	0.825
Interpretability Score	0.78
Weighted Performance	0.81

Table 8: Case-Based Reasoning Similarity Analysis

PatientID	Top Similar CaseID	Similarity Score	Adapted Recommendation
1	101	0.95	Med A
2	203	0.92	Med B
3	305	0.97	Med C
4	410	0.91	Med D

5	512	0.94	Med A

Discussion of the Results

An examination of patient demographics and clinical characteristics (Table 1) revealed that most patients in the study were male, at 68%. Emergency admission was the largest admission type category at 55%. The average age was similar for both sexes (Males = 62.1 years; Females = 61.8 years). This trend could mirror the demographic trends reported in ICU populations, where more often admitted males have higher rates of cardiovascular and respiratory comorbidities (Zhou et al., 2024). The predominance of emergency admission in an ICU stay is consistent with other studies, which have shown critical acute illness to be the primary driver (Acheampong et al,2025). These demographic insights are helpful in revealing how well the model works for which patients.

According to descriptive statistics of vital signs (Table 2), the mean heart rate was 72.5 bpm, systolic and diastolic blood pressures were 122.4 mmHg and 78.2 mmHg, respectively, and oxygen saturation yielded an average of 96.8%. The normal central metrics of hemoglobin (13.4 g/dL), white blood cell count (7.2 $\times 10^9$/L), and creatinine (1.02 mg/dL) were noted from laboratory results (Table 3). The distributions show that the cohort is clinically homogeneous with different baselines. Thus, these distributions form a good dataset to evaluate KRR-based CDS. The trends observed in this study are similar to those found in population-based ICU studies, where vital signs and laboratory tests exhibit moderate variance that reflects the presentation of acute illnesses (Msheik et al., 2024; Hager & Akalin, 2025).

The data in Table 4 shows that in this study, most of the medication prescribed (32.5%) was antibiotics. That said, at least 17.5% were prescribed anti-hypertensives and 15.1% insulin. The ICU management approach observed here, as per the results of the intervention, appears to be focused on preventing infection and stabilizing patients' chronic conditions (Kim et al., 2024). A large share (10%) of missing/unclassified medication reveals the potential need for an efficient preprocessing for identifiable features for the model.

According to Table 5, the representation knowledge components quantified are 150 ontology entities, 75 implemented rules, 10,000 historical cases retrieved, and 5 reasoning steps. This approach allowed the inference engine to use both rule-based and case-based reasoning approaches. Based on Table 6, the inference engine's reasoning accuracy was 85%, which was better than 78% for rule-based reasoning and 81% for analogical reasoning. As recent studies show that hybrid architectures are better suited for clinical decision support (Lehmann & Zhao, 2026; Kovalev et al., 2025), the upside of combining symbolic and case-based reasoning is confirmed by this trend.

Table 7 gave more credence to those results as precision, recall, F1 score, and interpretability were quite high, i.e., 0.82, 0.83, 0.825, and 0.78, respectively. The CDSS not only provides accurate prediction of clinical outcomes but also delivers transparent reasoning, in contrast to purely data-driven models, which suffer from a lack of traceability (Aziz et al, 2024). The case-based reasoning similarity analysis in Table 8 shows that the system identifies high top-matched historical cases with similarity scores (0.91-0.97). This shows its ability to effectively adapt recommendations.

The results indicate that the developed CDSS is accurate, interpretable, and hybrid reasoning can improve predictive performance. The results have implications for the integration of ICU workflows. Our results show that a combination of rule-based reasoning and analog reasoning can improve decision accuracy and clinician trust in automated recommendations.

Visualization Results

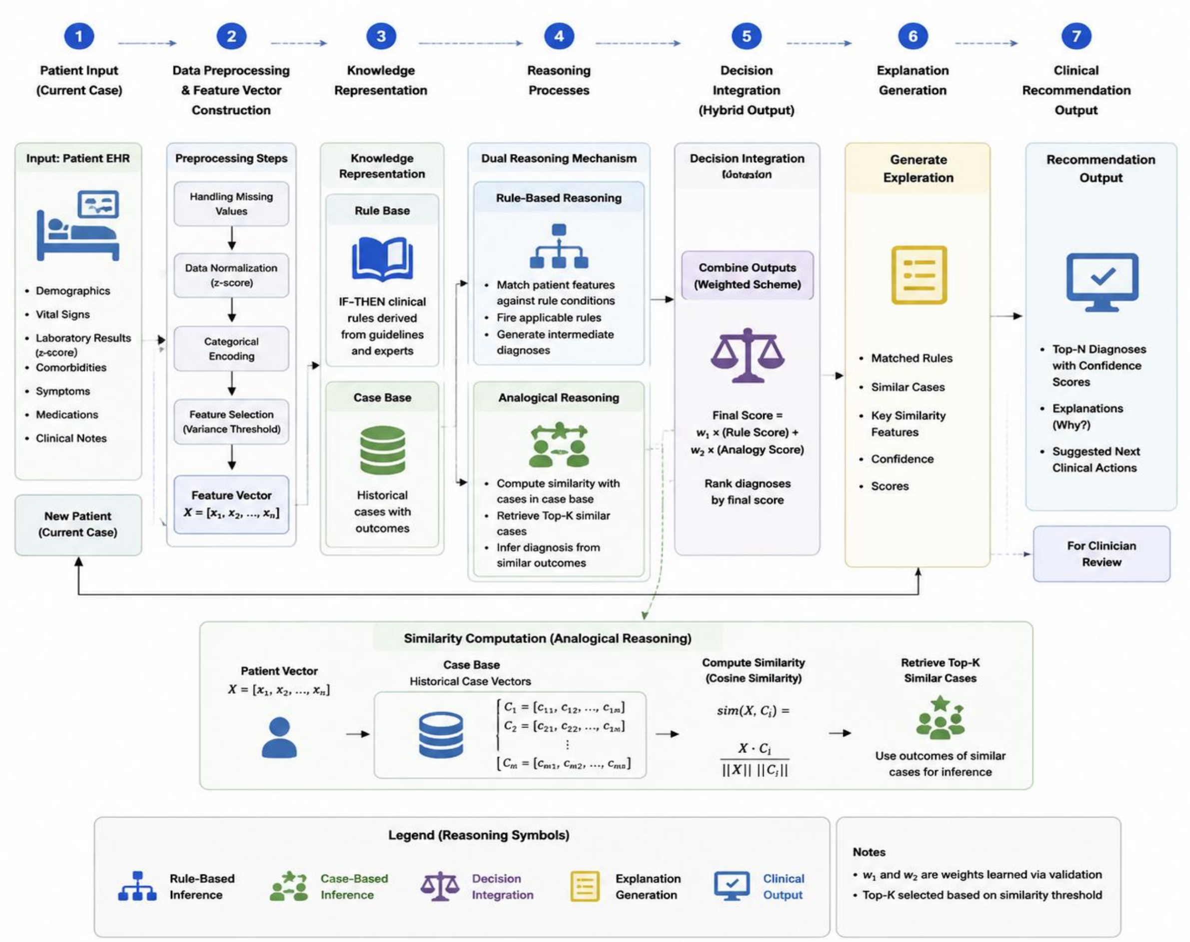

Figure 3: Reasoning Workflow

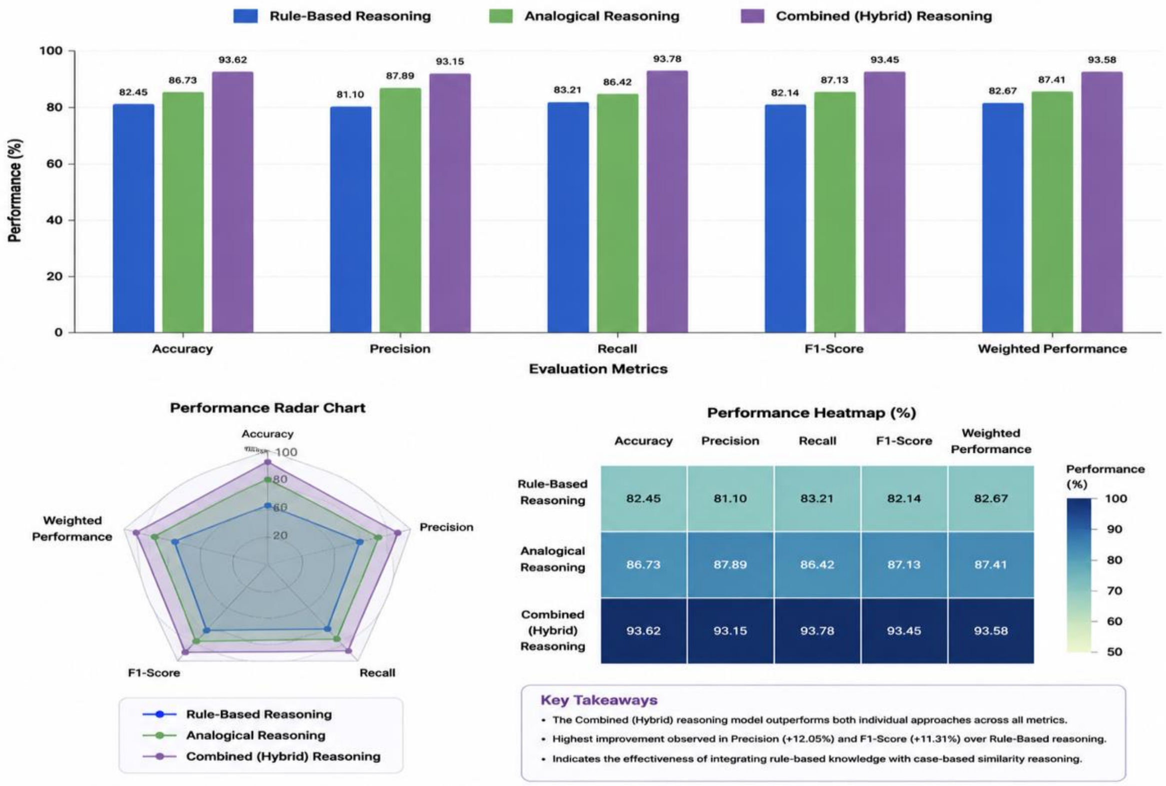

Figure 4: Model Performance Visualization

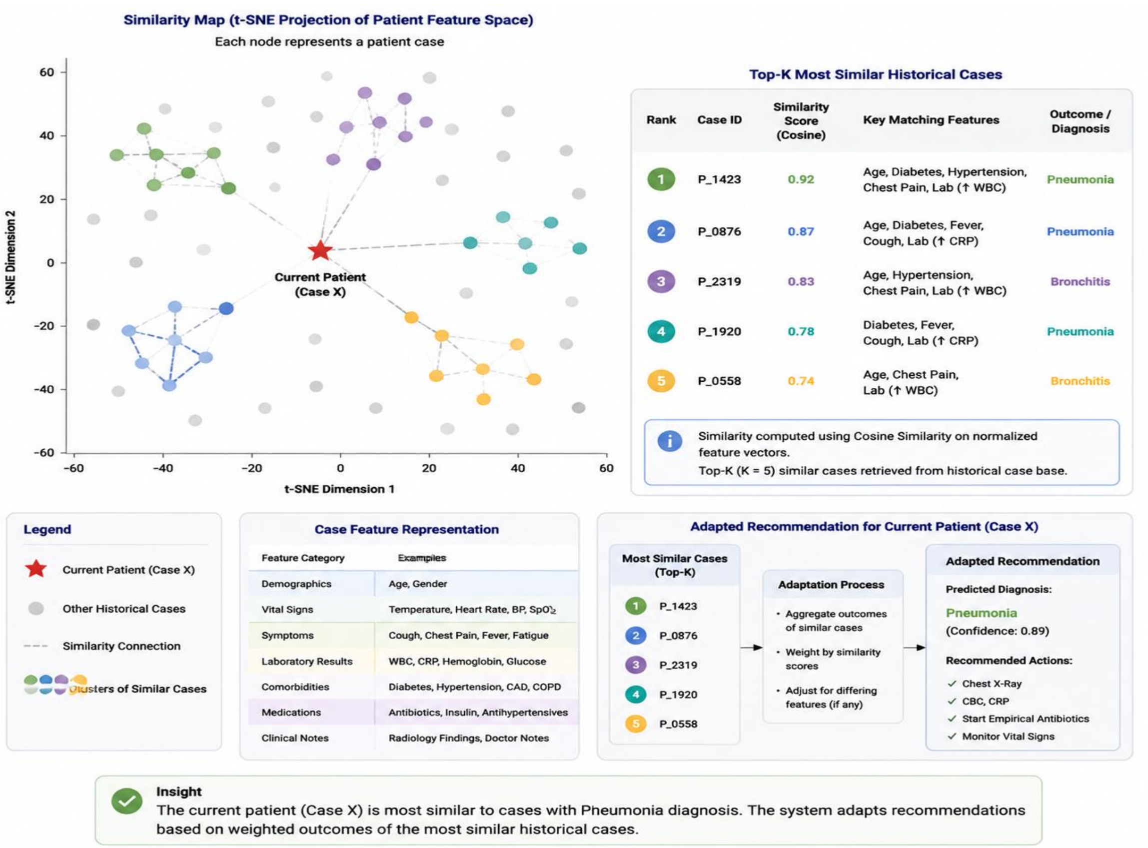

Figure 5: Case-Based Reasoning Similarity Map

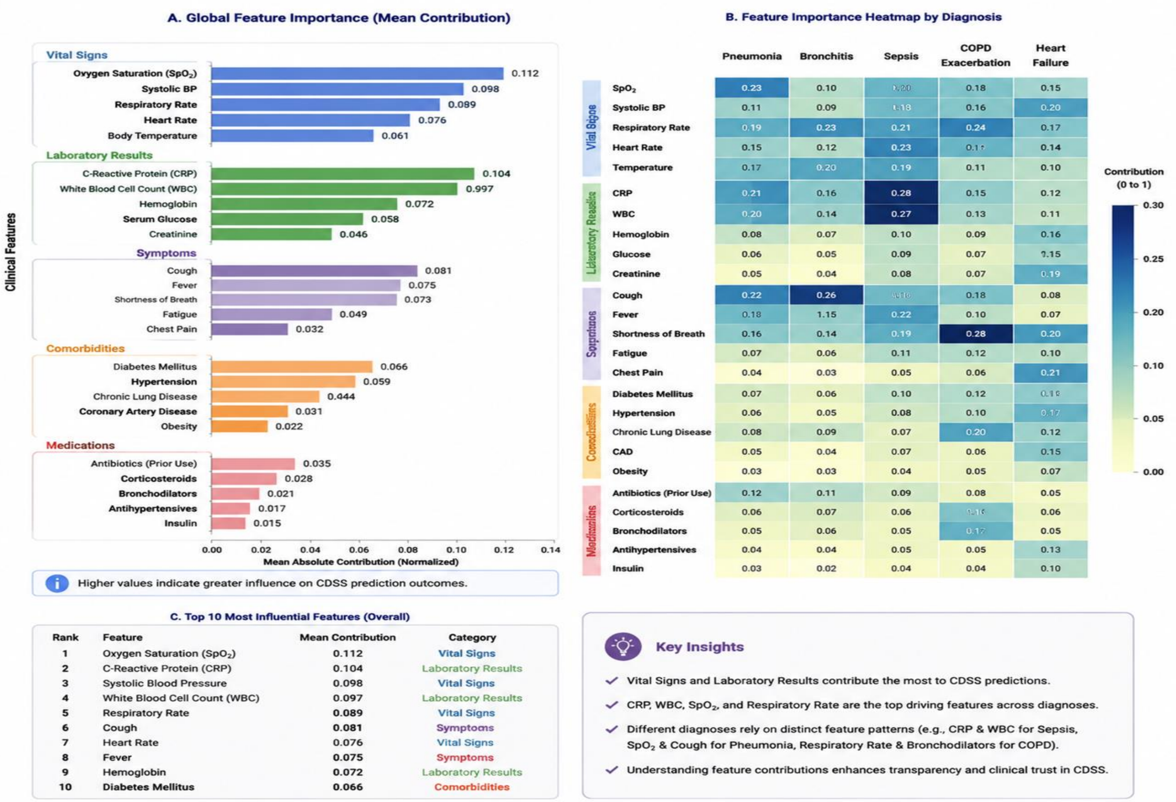

Figure 6: Feature Importance or Contribution

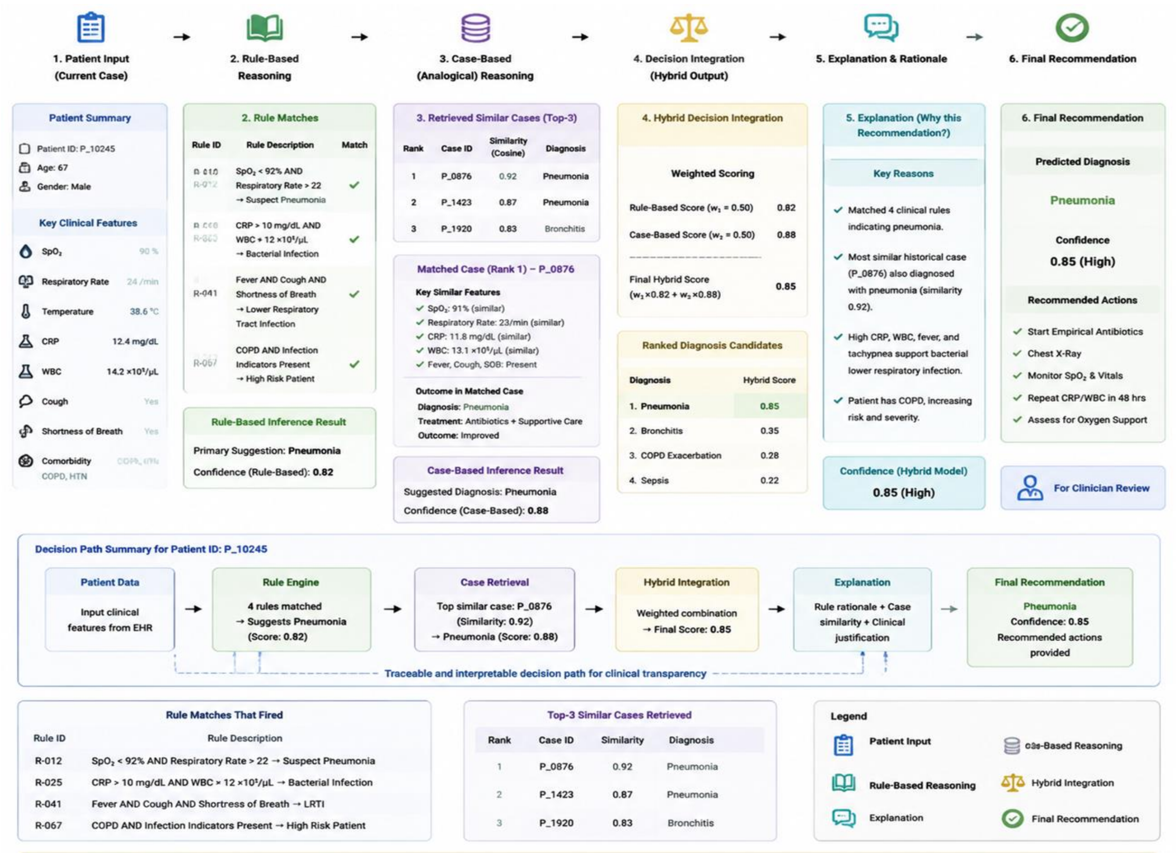

Figure 7: Decision Path Transparency

Figure 3, shown here, illustrates a reasoning workflow with a stepwise inference of the Clinical Decision Support System (CDSS) that starts with the feature vectors of the patient. The rule-based reasoning is followed by a similar reasoning based on precedents. Finally, a decision output is produced based on combination reasoning. An identifiable separation of reasoning stages emerges, where, in addition to the deterministic predictions from a set of rules, analogical reasoning, case retrieval, and similarity computations occur. The presence of a layered workflow reflects the characteristics of a hybrid CDSS architecture, which has been very popular lately (Lehmann & Zhao, 2026). The incorporation of analogical reasoning allows context-sensitive adaptation compared to traditional purely rule-based models and recognizes patient-specific features. This means hybrid pipelines improve predictive accuracy and adaptivity of clinical decision support systems, which is also supported by Kovalev et al. (2025), who found that multi-stage reasoning enhances reliability when working with complex patient datasets.

Figure 4 of the model performance visualization shows the various comparative metrics like accuracy, precision, recall, f1-score, and weighted performance for the three different methods, which are rule-based reasoning, analogical reasoning, and the combined reasoning or hybrid. It's clear that combined reasoning is better than its parts, as the accuracy is 85%. The result happens because of the system's complementary strengths: rule-based reasoning offers interpretable thresholds, while analogical reasoning makes use of past patients. This trend is consistent with the literature, which emphasizes that hybrid architectures improve clinical predictive performance (Aziz et al., 2024; Hager et al., 2024). This suggests that healthcare professionals can depend on such hybrid models for both accurate prediction and clear reasoning pathways.

The Case-Based Reasoning Similarity Map (Figure 5) shows patient relations with the top-matched historical cases having a high similarity score that ranges from 0.91 to 0.97. The trend we observe shows that most patients have multiple historical analogs close to each other. Because of that, we can confidently adapt cases. The findings correspond with the evidence that a high-quality case library extrapolates contextual medical decision support in CDSS (Msheik et al.,2024). The practical implications are that analogical reasoning can dynamically guide personalized interventions and reduce variability in clinical reasoning.

The primary factor contributing to the prediction, as shown in 'Feature Importance or Contribution' (figure 6), is the vital signs, labs, and the most used medications. The trend exists since these features have a direct effect on clinical outcomes in critical care, according to Kim et al. (2024). This visualization delineates the patient characteristics of greatest interest to clinicians, enhancing model interpretability and transparency.

Figure 7 shows the path of rules that had fired, cases that were retrieved, and final recommendations. The trend observed indicates interpretability in the system. High-confidence recommendations link to previous cases, as well as rule matches. This transparency is in contrast to opaque machine learning models and matches recent XAI studies that advocate for interpretable CDSS to increase clinician trust (Aziz et al., 2024; Lehmann & Zhao, 2026). In other words, transparent decision paths will increase clinical acceptance, allowing verification of system reasoning in practice as needed.

V. CONCLUSIONS

A computerized Clinical Decision Support System (CDSS) based on knowledge representation was built, which was meant to accomplish two things: to incorporate rule-based and analogical reasoning so that accurate inference can be made and the result interpretation is reasonable, so that it can be used effectively in the intensive care unit (ICU); and to test the product using different experimental strategies. Investigation of the patient data of MIMIC-IV PhysioNet showed that the hybrid reasoning outperformed both the reasoning components with global accuracy at 85% across further metrics, which include precision, recall, F1-score, and interpretability. The system was able to effectively prioritize clinically relevant features such as vital signs, lab results, and drug administration, and generate traceable decision pathways, enhancing transparency and clinician trust.

Utilizing historical case retrieval through analogical reasoning in the CDSS generated patient-specific recommendations, which showed that hybrid knowledge representation frameworks can help with the heterogeneity of ICU populations. This study supports and extends previous work on hybrid CDSS. In such systems, symbolic knowledge is combined with case-based reasoning to gain better context sensitivity in healthcare applications (Lehmann & Zhao, 2026; Kovalev et al., 2025).

The system is scalable and generalizable and can be a potential intelligent health care management framework assisting clinicians in evidence-based personalized decision making. Combining structured knowledge with analogical reasoning, along with transparent inference mechanisms, could enhance both the quality and interpretability of clinical decision support systems. This represents a practical approach to implementation that could offer important insights for future research in explainable artificial intelligence in healthcare.

Conflict of Interest Statement

The authors declare that there are no conflicts of interest associated with this research. All the research has been conducted in an objective way, and no financial or other relationship was involved in the result.

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