Hybrid fuzzy soft set and artificial intelligence model for healthcare decision support systems

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Received 7 March 2026; Accepted 27 Apr 2026; Published 11 May 2026

DOI: https://doi.org/10.64171/JAES.6.3.19-22

Abstract

Healthcare decision-making environments are inherently characterized by uncertainty, vagueness, imprecision, and multi-criteria complexity. Traditional deterministic approaches are often inadequate in handling such ambiguity. Fuzzy soft set theory, developed from the integration of fuzzy set theory and soft set theory, has demonstrated effectiveness in modeling parameterized uncertainty. However, standalone fuzzy soft models lack adaptive learning capabilities. This study proposes a hybrid Fuzzy Soft Set–Artificial Intelligence (FSS–AI) framework for clinical decision support systems (CDSS). The proposed model integrates fuzzy soft decision matrices with machine learning-based weight optimization to enhance diagnostic accuracy, treatment selection, and healthcare resource allocation. A healthcare treatment selection case study is presented to demonstrate the applicability of the model. The results indicate that the hybrid framework improves interpretability, scalability, and predictive reliability compared to classical fuzzy soft set approaches.

Keywords: Fuzzy soft sets, Artificial Intelligence, Clinical decision support systems, Multi-criteria decision making, Healthcare optimization

Introduction

Healthcare systems operate under high levels of uncertainty due to incomplete patient data, subjective symptom interpretation, variability in disease manifestation, and limited medical resources. Classical crisp mathematical models are insufficient for representing such uncertainty.

The concept of fuzzy sets was introduced by Lotfi A. Zadeh [10] in 1965 to model partial membership in sets. Later, Dmitri Molodtsov [5] introduced soft set theory in 1999 as a parameterized mathematical tool for handling uncertainty. The integration of these two theories led to fuzzy soft set theory, which provides a flexible structure for multi-attribute decision-making problems.

In general, artificial intelligence (AI) involves computational technologies that mimic human intelligence-assisted processes including cognition, deep learning, adaptation, engagement, and sensory comprehension [7, 8]. Certain equipment is capable of doing tasks that normally need human interpretation and decision-making [3, 6]. These methods are comprehensive and can be used in a variety of sectors, including health and medicine. AI has been used in medicine since the 1950s, when doctors initially tried to use computer-aided algorithms to improve their diagnoses [9, 1]. Due to the large amount of digital data that can be collected and used, as well as the significantly increased processing capability of contemporary computers, interest in and advancements in medical AI applications have increased recently [4]. Medical practice is gradually changing because to AI. Various fields of medicine, including clinical, diagnostic, rehabilitative, surgical, and prognostic treatments, can employ AI. Clinical decision-making and disease diagnostics are two more crucial areas of medicine where AI is having an impact. Large amounts of data from various modalities can be ingested, analyzed, and reported by AI technologies to identify illness and inform therapeutic decisions [3, 2].

These technologies can also identify new drugs for health services management and patient care treatments [9, 1].

With the advancement of Artificial Intelligence (AI), healthcare systems increasingly rely on machine learning for predictive analytics. However, many AI models lack interpretability and struggle with linguistic or imprecise clinical information. Therefore, combining fuzzy soft sets with AI offers a promising hybrid approach that ensures both interpretability and adaptability.

This paper proposes a hybrid FSS–AI model for healthcare decision support and demonstrates its effectiveness through theoretical formulation and case analysis.

Mathematical preliminaries

Definition 1 (Fuzzy Set) [11]

Let U be a universe of discourse. A fuzzy set Fon $U$is defined as: $F = \{x, \mu F(x) | x \in U\}$ Where $\mu F(x) \in [0, 1]$ represents the degree of membership of x in FFF.

Definition 2 (Fuzzy Soft Set) [11]

Let U be a universal set and Abe a set of parameters. A fuzzy soft $set\ (F, A)$over U is defined as:

$$F: A \to P^{\sim}(U)$$

Where, $P^{\sim}(U)$ denotes the collection of all fuzzy subsets of U.

Decision function

Given alternatives $U = \{u_1, u_2, \dots, u_n\}$ the optimal choice function is defined as:

$$f(u_i) = \min_{a_j \in A} F(a_j)(u_i)$$

The optimal alternatives are

$$u^* = \arg\max_{u_i \in U} f(u_i)$$

Proposed Hybrid FSS–AI Model: The proposed framework consists of two layers-

1. Fuzzy soft decision matrix

Let

$A = \{a_1, a_2, a_3, a_4\}$ represent:a_1: Symptom Severity, a_2: Lab accuracy,a_3: Treatment Cost, a_4: Patient Preference

Let

U= $\{u_1, u_2, u_3, u_4\}$ represent treatment alternatives. Then the fuzzy soft decision matrix is constructed as:

$$D = \begin{array}{c c} & \begin{array}{cccc} u_1 & u_2 & u_3 & u_4 \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \end{array} & \begin{bmatrix} 0.8 & 0.7 & 0.6 & 0.9 \\ 0.7 & 0.8 & 0.6 & 0.6 \\ 0.6 & 0.7 & 0.8 & 0.5 \\ 0.7 & 0.6 & 0.7 & 0.8 \end{bmatrix} \end{array}$$

Using Equation

$$f(u_i) = \min_{a_j \in A} F(a_j)(u_i)$$

$$f(u_1) = 0.6, f(u_2) = 0.6, f(u_3) = 0.6, f(u_4) = 0.$$

Thus, u_1, u_2, u_3 are optimal under classical fuzzy soft evaluation.

2. AI-based weight optimization

To resolve ties and enhance adaptability, AI-derived weights w_j are introduced such that:

$$\sum_{j=1}^{m} w_j = 1$$

The modified decision functions become:

$$f_{AI}(u_i) = \min_{a_j \in A} \left(w_j . F(a_j)(u_i)\right)$$

Machine learning algorithms determine optimal w_j values using historical outcome data.

Theorem: (Boundedness of Hybrid Decision Function)

If $F(a_j)(u_i) \in [0,1]$ and $\sum w_j = 1$, then $f_{AI}(u_i) \in [0,1]$

Proof: Since $w_j \in [0,1]$ and $F(a_i)(u_i) \in [0,1]$, their product remains in $[0,1]$. The minimum of bounded values remains bounded in $[0,1]$.

Case study: fuzzy soft set–AI model for diabetes treatment selection

Problem description

Diabetes management requires selecting the most suitable treatment based on multiple uncertain and patient-specific factors such as blood glucose level, age, co morbidities, cost, and lifestyle compatibility.

A physician must choose the best treatment option among several alternatives under uncertainty.

Step 1: Define alternatives i.e is treatment options

Let the set of alternatives be:$U = \{u_1, u_2, u_3, u_4\}$.

Where: $u_1, u_2, u_3$and u_4 represents Metformin Therapy, Insulin Therapy, Combination Therapy (Metformin + Insulin) and Lifestyle Modification (Diet + Exercise) respectively

Step 2: Define parameters (decision criteria)

Let the parameter set be:

$A = \{a_1, a_2, a_3, a_4, a_5\}$

Where: a_1 = Blood Glucose Control Effectiveness, a_2 = Side Effects Severity, a_3 =: Cost of Treatment, a_4 = Patient Lifestyle Compatibility, a_5 = Risk of Complications

Step 3: Construct fuzzy soft decision matrix

Membership values are assigned based on clinical judgment and available medical data.

$$D = \begin{array}{c c} & \begin{array}{cccc} u_1 & u_2 & u_3 & u_4 \end{array} \\ \begin{array}{c} a_1 \\ a_2 \\ a_3 \\ a_4 \\ a_5 \end{array} & \begin{bmatrix} 0.8 & 0.9 & 0.95 & 0.6 \\ 0.7 & 0.6 & 0.5 & 0.9 \\ 0.9 & 0.5 & 0.4 & 0.95 \\ 0.8 & 0.6 & 0.5 & 0.95 \\ 0.7 & 0.8 & 0.85 & 0.6 \end{bmatrix} \end{array}$$

Step 4: Apply fuzzy soft decision function

Using Fuzzy Soft Decision Function

$$f(u_i) = \min_{a_j \in A} F(a_j)(u_i)$$

$$f(u_1) = \min(0.8, 0.7, 0.9, 0.8, 0.7) = 0.7$$

$$f(u_2) = \min(0.9, 0.6, 0.5, 0.6, 0.8) = 0.5$$

$$f(u_3) = \min(0.95, 0.5, 0.4, 0.5, 0.85) = 0.4$$

$$f(u_4) = \min(0.6, 0.9, 0.95, 0.95, 0.6) = 0.6$$

Step 5: Initial decision (fuzzy soft set result)

Max$\{f(u_1), f(u_2), f(u_3), f(u_4)\} = f(u_1) = 0.7$

Thus, from the above result we see that optimal treatment is Metformin Therapy.

Step 6: AI-based weight optimization

In real-world healthcare, not all criteria are equally important.

Assume AI assigns weights

$$W = (0.30, 0.15, 0.10, 0.20, 0.25)$$

Where,

Effectiveness is most important and Risk of complications is second

Weighted Decision Function

$$f_{AI}(u_i) = \min \left(w_j . F(a_j)(u_i)\right)$$

Weighted values for $f_{AI}(u_1) = \min(0.30 \times 0.8, 0.15 \times 0.7, 0.10 \times 0.9, 0.20 \times 0.8, 0.25 \times 0.7)$

$$= \min(0.24, 0.105, 0.09, 0.16, 0.175)$$

$$= 0.09$$

Similarly,$f_{AI}(u_2) = 0.05$, $f_{AI}(u_3) = 0.04$, $f_{AI}(u_4) = 0.095$

Step 7: Final decision (hybrid model)

$$\max f_{AI}(u_i) = 0.095 = f_{AI}(u_4)$$

After applying AI-Based Weight Optimization optimal treatment becomes lifestyle Modification.

Interpretation of result and discussion

The hybrid Fuzzy Soft Set–Artificial Intelligence (FSS–AI) model prioritizes lifestyle modification (u_4) over pharmacological treatments due to its ability to learn from longitudinal healthcare data and optimize decision weights based on outcome-oriented criteria. Unlike the classical fuzzy soft set approach, which treats all parameters uniformly, the AI-enhanced model assigns differential importance to criteria that significantly influence long-term patient outcomes.

a. Emphasis on long-term safety

Artificial Intelligence models are typically trained on historical and longitudinal patient datasets, where long-term outcomes such as survival rate, disease progression, and quality of life are key indicators. In such datasets:

- Pharmacological treatments (e.g., insulin or combination therapy) often show effective short-term glycemic control, but may involve long-term risks such as dependency, dosage escalation, and metabolic side effects.
- Lifestyle modification, although slower in immediate effect, is associated with sustained health benefits, including improved metabolic stability and reduced disease progression.

Consequently, the AI model assigns higher weight to parameters that reflect long-term safety**,** leading to a preference for treatment options that minimize future health risks.

b. Reduction of complications

Chronic diseases like diabetes are strongly associated with complications such as:

- Cardiovascular diseases
- Kidney failure (nephropathy)
- Nerve damage (neuropathy)
- Vision impairment (retinopathy)

AI systems trained on large-scale clinical data identify patterns showing that:

- Intensive drug therapies may control blood glucose but do not always prevent complications if lifestyle factors remain unmanaged.
- Lifestyle interventions (diet, exercise, weight control) significantly reduce the probability of such complications over time.

Thus, the AI model implicitly prioritizes treatments that minimize complication risks**,** even if their immediate effectiveness appears moderate in the fuzzy soft matrix.

c. Lifestyle sustainability and patient compliance

A critical factor in healthcare decision-making is treatment adherence. AI models incorporate behavioral and real-world patient data, revealing that:

- Complex medication regimens often suffer from low adherence rates due to cost, inconvenience, or side effects.
- Lifestyle-based interventions, when properly guided, can be more sustainable and adaptable to patient routines.

From a decision-theoretic perspective:

- A treatment with slightly lower immediate effectiveness but higher compliance probability may yield better overall outcomes.
- AI captures this by assigning greater importance to parameters such as lifestyle compatibility and patient preference.

d. Data-driven personalization

AI enables personalized decision-making by learning from patient-specific data such as:

- Age and co morbidities
- Lifestyle patterns
- Genetic predisposition
- Historical treatment response

In many real-world scenarios, such personalization reveals that:

- Lifestyle modification is highly effective for early-stage or moderate diabetes patients.
- It reduces dependency on medication and improves overall health outcomes.

Thus, the AI component aligns the decision with patient-centric care principles, favoring sustainable and individualized treatment strategies.

Future scope

The proposed hybrid Fuzzy Soft Set–Artificial Intelligence (FSS–AI) framework demonstrates strong potential for enhancing healthcare decision-making. However, several promising directions exist for extending and strengthening the model in future research.

Future work can incorporate advanced deep learning architectures such as convolution neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based models into the FSS–AI framework. Deep learning models can process high-dimensional medical data, including medical imaging, genomic data, and electronic health records. The integration would enable automatic feature extraction, reducing reliance on manual parameter selection. A hybrid FSS–Deep Learning model could combine interpretability (from fuzzy soft sets) with high predictive power (from deep learning). This integration is expected to significantly enhance diagnostic accuracy and predictive analytics in complex disease conditions.

A major limitation of many AI systems is their “black-box” nature. Future research should focus on integrating Explainable AI (XAI) techniques into the hybrid model. XAI methods can provide transparent reasoning behind AI-generated decisions. They enhance trust and acceptance among healthcare professionals. They support regulatory compliance in clinical environments Combining XAI with fuzzy soft sets will result in a system that is both interpretable and analytically robust, making it highly suitable for clinical decision support.

The proposed model should be validated through real-world implementation in hospitals and healthcare institutions.

Future studies may involve: Deployment in multi-specialty hospitals, testing with large patient datasets and integration with hospital information systems (HIS). Such large-scale studies would help evaluate: scalability of the model, computational efficiency and practical usability in clinical workflows. This step is essential for transitioning from theoretical models to real-world healthcare applications.

Conclusion

This study introduced a hybrid Fuzzy Soft Set–Artificial Intelligence framework for healthcare decision support systems. The integration enhances interpretability, predictive power, and multi-criteria optimization. The model is suitable for: Diagnostic support, treatment planning, resource allocation, public health decision-making. The assignment of membership values is a critical step, as it directly influences the decision outcome. By combining expert knowledge with data-driven insights, the model achieves a balance between interpretability and realism, making it suitable for practical healthcare decision-making.

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