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Linking Perception and Measurement: Real-World Validation of a Fuzzy Logic Model for Patient Satisfaction

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ABSTRACT: In modern healthcare, patient satisfaction is widely recognized as a cornerstone of healthcare quality assessment, influencing not only clinical outcomes but also institutional reputation and patient loyalty. Yet, its inherently subjective and multifaceted nature makes it difficult to capture with conventional tools. This study introduces an inference system, developed within the framework of artificial intelligence, to provide a more nuanced evaluation of patient-centered care. The model examines eight qualitative indicators of patient experience, including communication, accessibility, staff competence, and perceived treatment outcomes, translating them into measurable outputs through linguistic variables. Relying on a Mamdani approach combined with centroid defuzzification, the system generates an interpretable satisfaction score on a 0–10 scale. Applied to real-world clinical data, this approach proves effective in managing uncertainty, improving decision support, and offering a refined perspective for patient experience evaluation, ultimately supporting more responsive and human-centered healthcare delivery.

KEYWORDS: Patient-centered care, Inference system, Artificial intelligence, Healthcare quality assessment, Centroid defuzzification, Patient experience evaluation.

1 INTRODUCTION

Patient satisfaction has emerged as a central performance indicator in contemporary healthcare systems, directly influencing institutional accreditation, reimbursement schemes, and public trust [1], [2], [3]. Numerous studies have highlighted its association with improved adherence to treatment protocols, lower readmission rates, and better health outcomes [4]. However, measuring satisfaction remains a persistent challenge, as it encompasses inherently subjective perceptions, emotional responses, and culturally mediated expectations that elude rigid quantitative frameworks [5], [6].

Conventional evaluation methods, typically based on Likert-scale questionnaires or fixed-response surveys, are often criticized for their inability to capture the nuanced and non-linear nature of patient experience [7], [8], [9]. Factors such as communication clarity, staff empathy, waiting time, infrastructure, and billing transparency interact in complex and sometimes asymmetric ways, shaping each individual's satisfaction in ways not easily reducible to scalar ratings [10], [11].

In this context, fuzzy logic has emerged as a promising mathematical framework for handling linguistic uncertainty and qualitative judgment. By assigning partial membership values to concepts like "good," "moderate," or "poor," fuzzy systems can process vague or approximate information while maintaining computational rigor [12], [13]. This capability has already been applied in various healthcare domains, from clinical decision-making to resource allocation. Yet, its application to patient satisfaction remains relatively underexplored, especially when models are validated on real-world clinical data, which is essential to ensure robustness, credibility, and applicability in practical healthcare settings [14], [15].

This study presents a comprehensive fuzzy logic–based model specifically designed to evaluate patient satisfaction across eight key dimensions of the healthcare experience. Unlike prior works that rely exclusively on simulated data, our validation uses empirical data collected from multiple hospital departments, allowing for a realistic assessment of the model's interpretability, adaptability, and relevance to patient-centered quality management. The proposed system defines and calibrates a set of fuzzy linguistic variables grounded in the literature and reviewed by healthcare professionals, and employs a rule-based Mamdani inference engine with centroid defuzzification to produce a continuous satisfaction score.

The originality of this work lies in its operational modeling of patient experience through a fully implemented fuzzy inference system, tested against authentic patient-reported feedback. This approach ensures that the generated scores are not only mathematically consistent but also reflective of real clinical contexts, making them more actionable for healthcare administrators and policy-makers.

The remainder of this paper is organized as follows: Section 2 reviews the conceptual foundations and challenges associated with measuring patient satisfaction. Section 3 provides an overview of relevant literature on fuzzy logic applications in healthcare. Section 4 details the methodology, including input variable selection, fuzzy rule design, and system implementation. Section 5 reports the results of empirical validation with real-world data. The discussion in Section 6 addresses broader implications, limitations, and prospects for refinement. Finally, Section 7 concludes by summarizing the main contributions and suggesting avenues for future research.

2 Patient Satisfaction In Healthcare: Concepts And Challenges

Patient satisfaction has become a cornerstone metric for assessing healthcare quality, reflecting patients' perceptions of care across dimensions such as clinical effectiveness, clarity of communication, service responsiveness, and the emotional climate in which care is delivered [16]. Beyond its role as a performance indicator, it is closely linked to treatment adherence, health outcomes, and the reputation of healthcare institutions [17]. However, its measurement remains inherently complex due to its subjective, multidimensional, and culturally sensitive nature.

Conceptual models have been instrumental in shaping assessment practices. The SERVQUAL framework, for instance, identifies five dimensions: tangibility, reliability, responsiveness, assurance, and empathy. In healthcare, these have been adapted to capture critical touchpoints such as appointment scheduling, waiting time, patient–staff interactions, and the physical environment of the facility [18], [19]. Similarly, Donabedian's structure, process and outcome model situates satisfaction within a broader framework of healthcare system performance, linking infrastructure and processes to patient-perceived outcomes [20].

Despite their utility, standardized instruments such as Likert-scale surveys often fall short of capturing the full richness of patient experience. Differences in cultural interpretation, individual expectations, and emotional state can lead to inconsistencies, while ceiling effects, where scores cluster at the upper end, limit the capacity to identify areas needing improvement [21], [22]. Moreover, satisfaction is dynamic, shaped not only by clinical results but also by prior encounters with the healthcare system.

Recent studies advocate for more adaptive and nuanced evaluation tools. While narrative feedback and open-ended responses offer deep insights, they remain difficult to process systematically. This has led to growing interest in computational approaches, notably fuzzy logic, which can capture the imprecision and gradations inherent in patient feedback [23]. Unlike binary or rigid categorical ratings, fuzzy models allow degrees of satisfaction to be expressed and aggregated, offering a representation more aligned with human reasoning.

Furthermore, fuzzy inference systems can integrate multiple dimensions of satisfaction into a single, interpretable score without oversimplifying the underlying complexity [24]. Such capabilities make them highly relevant for decision-support tools aimed at enhancing service delivery, identifying improvement priorities, and tailoring care pathways [25], [26], [27], [28].

3 Related Work

Assessing patient satisfaction remains a persistent challenge in healthcare, largely due to its inherently subjective, multidimensional, and linguistically nuanced nature. Conventional assessment methods, typically based on crisp numerical scores or rigid ordinal surveys, have often been criticized for oversimplifying complex human perceptions and neglecting contextual subtleties [29], [30]. In this regard, fuzzy logic has emerged as a particularly attractive alternative, offering a formal mechanism to represent uncertainty and capture linguistic granularity in patient feedback [31].

Over the past decade, several studies have demonstrated the versatility of fuzzy logic in modeling diverse dimensions of healthcare quality. Alkafaji and Al-Shamery proposed a fuzzy inference framework to assess satisfaction across multiple hospital departments [14], while Alonso and Magdalena provided a comprehensive review of fuzzy applications in healthcare decision-making, highlighting their interpretability and flexibility [15]. In a similar vein, Djam and Kimbi designed a fuzzy expert system for malaria management, effectively encapsulating the uncertainty inherent in medical diagnoses [32]. Yao and Kumar further illustrated the adaptability of fuzzy rule-based systems by optimizing clinical care pathways [33].

More recent research has explored integrating fuzzy logic with intelligent systems and multi-agent modeling. Cui and Tan developed a fuzzy decision support system for hospital service quality management, emphasizing multi-criteria evaluation and service improvement [34]. Ortiz-Barrios et al. applied a hybrid fuzzy multi-criteria decision-making approach to achieve a balanced assessment of both quantitative and qualitative healthcare indicators [35]. Neto et al. embedded fuzzy decision layers within intelligent diagnostic systems to enhance robustness and transparency [36], while Hernandez-Leal et al. investigated fuzzy logic–based triage decision-making under strict time constraints [37].

In the context of mobile and digital health, fuzzy logic has been increasingly used to interpret sensor-derived data, analyze real-time patient feedback, and deliver adaptive recommendations [38]. For example, Abdalla et al. combined fuzzy rule bases with IoT-enabled monitoring to improve home care services [39], and Tkachenko and Kovalyshyn designed a fuzzy-logic-driven platform to synthesize patient satisfaction across physical, emotional, and procedural domains [40]. These applications highlight the value of fuzzy reasoning in enabling personalized and adaptive care delivery.

The explainability of fuzzy systems is particularly critical in healthcare, where transparent reasoning fosters trust and accountability [41], [42]. Herrera and Verdegay have argued that fuzzy linguistic modeling not only offers mathematical rigor but also aligns closely with the way humans naturally express judgments [43]. This interpretability has inspired the development of satisfaction models tailored to specific cultural and linguistic contexts. For instance, Oluwagbemi et al. created a multilingual fuzzy-based decision support system for HIV diagnosis in indigenous South African communities, demonstrating the importance of culturally sensitive approaches in sub-Saharan healthcare [44].

Hybrid frameworks that combine fuzzy logic with machine learning are also gaining traction. Ala explored fuzzy-based multi-agent architectures to simulate outpatient appointment scheduling, showing their potential to optimize patient flow and resource allocation [45]. Improta et al. applied a fuzzy logic–based clinical decision support system to assess renal function in post-transplant patients, offering a design that could be adapted for satisfaction analysis in similar clinical settings [46]. Other researchers have proposed combining fuzzy systems with neural networks or evolutionary algorithms to improve parameter optimization and model adaptability [47].

Despite these advances, many previous works still rely on generic satisfaction criteria, use inflexible survey instruments, or remain detached from institutional implementation realities. Few models offer a modular fuzzy architecture that can be directly customized by healthcare professionals to reflect the specific needs of their patient population.

The present work addresses these limitations by introducing a modular fuzzy logic–based satisfaction evaluation framework grounded in eight rigorously selected criteria from validated literature. Each input is represented through tailored membership functions, and the inference engine generates a global satisfaction score based on linguistically interpretable rules. A distinctive feature of this contribution is its ability to produce automated, near-instantaneous scores, enabling smooth integration into interactive tools or decision-support dashboards. By emphasizing adaptability, transparency, and operational relevance, the proposed model provides a reproducible and customizable alternative to more rigid approaches, thereby advancing the state of patient-centered quality assessment.

4 Methodology

Fuzzy logic provides a robust paradigm for modeling subjective and linguistically imprecise assessments, making it particularly suitable for evaluating patient satisfaction. Unlike rigid numerical scoring, fuzzy systems enable the translation of nuanced human perceptions, often expressed in qualitative terms, into mathematically tractable formats [48]. This section describes the methodological framework used to design and implement the fuzzy satisfaction system. It details the process of selecting and normalizing variables, building membership functions and inference rules, implementing the computational engine, and performing evaluations based on real-world clinical data.

4.1 Selection And Normalization Of Linguistic Variables

The model relies on eight main input variables, identified through exploratory consultations with healthcare professionals and an extensive literature review [13], [49] Each variable corresponds to a thematic dimension commonly discussed in the literature on patient satisfaction and collectively integrates 30 elementary indicators [14], [50]. This design balances system simplicity with comprehensive coverage of key aspects of patient experience.

All variables were derived from actual measurements and patient feedback collected in the clinical setting, then normalized to a [0; 10] interval to ensure consistency among membership functions and comparability across heterogeneous dimensions. Table 1 presents the eight input variables and the output variable used in the fuzzy system.

Table 1. Overview of Linguistic Variables

No.	Variable Name	Universe of Discourse	Justification
1	Communication and Information	[0 ;10]	Clarity, active listening, and staff responsiveness to patient inquiries.
2	Reception and Accessibility	[0 ;10]	Ease of access, waiting time, and admission flow.
3	Staff Competence	[0 ;10]	Clinical expertise, professionalism, and empathy.
4	Environment and Infrastructure	[0 ;10]	Comfort, hygiene, and physical condition of the facilities.
5	Perceived Treatment Outcome	[0 ;10]	Patient-perceived effectiveness of received care.
6	Cost and Billing Transparency	[0 ;10]	Value for money and transparency of billing.
7	Patient Involvement and Personalized Care	[0 ;10]	Patient participation in medical decision-making.
8	Intention to Return and Recommend	[0 ;10]	Loyalty and likelihood of recommending the clinic.
9	Overall Patient Satisfaction (output)	[0 ;10]	Fuzzy aggregate output reflecting the perceived level of satisfaction.

To maintain coherence, variables originally expressed in different units (such as minutes or local currency) were converted from actual recorded values using linear transformations and context-specific thresholds. This approach preserves semantic meaning while ensuring compatibility with fuzzy inference and an intuitive scale from 0 (total dissatisfaction) to 10 (maximum satisfaction) [51], [52].

4.2 Definition Of Membership Functions

The shape of each membership function was selected based on the perceptual nature of the corresponding criterion:

- **Triangular functions** were used for criteria with clearly linear progression, such as communication or overall satisfaction.
- **Trapezoidal shapes** were chosen for dimensions with broader zones of acceptability (e.g., reception, infrastructure).
- **Gaussian functions** were applied to model staff competence, reflecting an ideal-centered subjective evaluation.
- **Sigmoid and inverse-sigmoid functions** were used for variables with progressive or asymmetric trends, such as perceived cost or treatment effectiveness.

These choices are grounded in both theoretical and applied fuzzy logic literature [47], [48], [49], [50], and were calibrated through expert feedback and academic references, including seminal works by Suzuki and Negishi [23] and Bouchon-Meunier and *al [*51*].* The corresponding membership functions are illustrated in the figures 1.

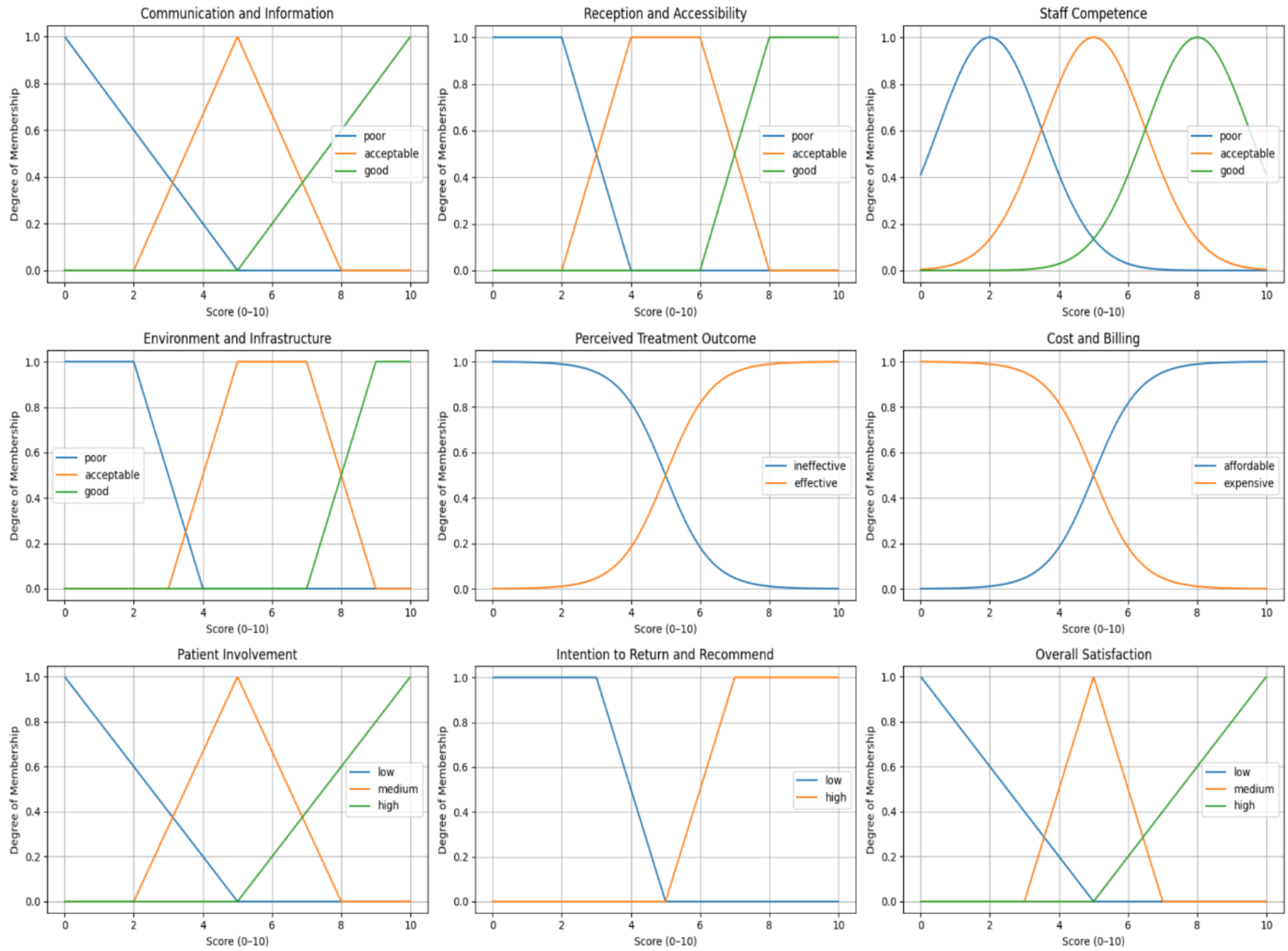

Fig. 1. Membership functions for the eight entry variables and the output variable

4.3 Construction Of The Rule Base

The fuzzy rule base defines the logical relationships between input variables and the system's output. It consists of predicates and conclusions expressed as combinations of propositions and logical operators [53]. The 15 representative rules were formulated using patterns observed in the real patient satisfaction data and supported by established theoretical models such as those of Donabedian and Parasuraman et al. [18], [19], [20]. These rules reflect qualitative associations frequently observed in clinical practice and align with current AI-driven healthcare evaluation approaches [54].

Table 2 presents a total of 15 fuzzy rules, selected as most representative of common clinical scenaios in the evaluation of patient satisfaction.

Table 2. Fifteen Representative Rules in the Fuzzy Inference Base

Rule	IF Clause (Predicates)	THEN Satisfaction
R1	IF Communication and Information is high AND Perceived Treatment Outcome is high AND Reception is high	High
R2	IF Communication and Information is low OR Perceived Treatment Outcome is low	Low
R3	IF Environment and Infrastructure is poor AND Reception and Accessibility is poor	Low
R4	IF Cost and Billing is expensive AND Perceived Treatment Outcome is low	Low
R5	IF Communication and Information is medium AND Perceived Treatment Outcome is medium	Medium
R6	IF Patient Involvement is high AND Communication and Information is high	High
R7	IF Intention to Return is low OR Environment and Infrastructure is poor	Low
R8	IF Reception and Accessibility is acceptable AND Perceived Treatment Outcome is high	Medium
R9	IF Cost and Billing is acceptable AND Treatment Outcome is medium AND Communication and Information is medium	Medium
R10	IF Communication and Information is low AND Reception is poor AND Cost is expensive	Low
R11	IF Intention to Return is high AND Patient Involvement is high	High
R12	IF Perceived Treatment Outcome is medium AND Environment and Infrastructure is high	Medium
R13	IF Communication and Information is high AND Cost and Billing is affordable	High
R14	IF Communication is medium AND Treatment Outcome is high	High
R15	IF Patient Involvement is low AND Reception is poor	Low

4.4 INFERENCE MECHANISM AND DEFUZZIFICATION

A Mamdani-type fuzzy inference engine was adopted due to its transparency and suitability for linguistic reasoning in clinical contexts. The reasoning process involves four classical stages:

Each input, based on actual patient-derived values, is transformed into a fuzzy set using its respective membership functions.

1. **Fuzzification**: Each input, based on actual patient-derived values, is transformed into a fuzzy set using its respective membership functions.
2. **Rule Evaluation**: Activation levels of the fuzzy rules are computed by applying the minimum operator to the degrees of membership of the rule's antecedents. This conjunctive approach aligns with clinical reasoning under uncertainty.
3. **Aggregation**: The output fuzzy sets of all activated rules are aggregated using the max–min composition method, ensuring that the system captures multiple interacting influences on satisfaction.
4. **Defuzzification**: The final output is derived through the centroid method (center of gravity), which calculates the balance point of the aggregated fuzzy area. This method was chosen for its robustness and widespread acceptance in medical fuzzy systems [32], [39].

This mechanism ensures interpretability, continuity, and alignment with the cognitive models through which human evaluators articulate satisfaction. Furthermore, the Mamdani framework supports rule traceability and explainability, which are essential for trust in clinical applications [55].

In future work, alternative inference mechanisms such as Sugeno-type systems may be explored to allow for more computational efficiency in embedded or real-time deployments, although they may offer less intuitive interpretability.

4.5 SYSTEM IMPLEMENTATION

The fuzzy satisfaction evaluation system was implemented in Python using the scikit-fuzzy library. Its modular, object-oriented design allows updates to membership functions, the rule base, or the inference engine without affecting the rest of the system.

Each patient profile corresponds to a real-world case collected from the participating healthcare facility, based on the eight normalized satisfaction dimensions. These variables were derived from patient survey responses and service performance indicators, then preprocessed to ensure completeness and consistency before integration into the fuzzy inference engine.

The Mamdani-type system processes these inputs, applying fuzzification, rule evaluation, aggregation, and defuzzification via the centroid method to produce a final satisfaction score between 0 and 10. Average computation time remains under 50 milliseconds per patient, ensuring suitability for integration into clinical dashboards or patient monitoring tools.

Grounded in actual patient feedback and operational data, the system produces outputs that are mathematically coherent and contextually meaningful, enabling healthcare managers to monitor satisfaction trends and support decision-making.

4.6 Mathematical Components Of The Fuzzy System

The fuzzy system developed in this study is built upon a Mamdani-type inference mechanism, a well-established framework in applications requiring subjective and qualitative decision-making. The inference process follows a structured sequence comprising four fundamental stages.

Stage 1: Input Fuzzification

Each input variable $x_i \in [0,10]$ is mapped to a fuzzy value using a membership function $\mu_{A_i}(x_i)$.

For instance, for the linguistic category *Good* of a variable such as *Communication and Information*:

$$\mu_{Good}(x) = \begin{cases} 0, if\ x \leq 4, \\ \frac{x-4}{2}, if\ x < x < 6, \\ 1, if\ x \geq 6\,. \end{cases} \quad (1)$$

Stage 2: Evaluation of Fuzzy Rules

A fuzzy rule can be intuitively expressed as:

$R_k\ :\ IF\ x_1\ is\ A_1^k$ AND $x_2\ \ is\ \ A_2^k$ AND... AND $x_n\ is\ \ A_n^k$, THEN y is B^K (2)

Formally, for any number of inputs:

R_k: IF $\wedge_{i=1}^{n} [\![(x_i\ is\ A_i^k]\!]) THEN$ y is B^k (3)

The activation degree $\alpha_K\ of\ rule\ \ R_k\ is\ given\ by$:

$$\alpha_k\ =\ \min_{i=1\ldots n} \mu_{A_i^k}\ (x_i) \quad (4)$$

Stage 3: Aggregation of Rule Outputs

The fuzzy outputs of activated rules are aggregated using a max–min composition:

$$\mu_B(y) =\ \max_k [\![(min]\!] [\![(\alpha]\!]_k, \mu_{B^{k(y)}})) \quad (5)$$

where $\mu_{B^K}(y)$ denotes the membership function of output B^k.

Stage 4: Defuzzification

The final, crisp output y^*, representing the estimated level of satisfaction, is obtained via the centroid method:

$$y^*\ = \frac{\int y \mu_B(y) dy}{\int \mu_B(y) dy} \quad (6)$$

This rigorous modeling translates linguistic judgments into operational reasoning, making it suitable for implementation within an AI-based system focused on patient satisfaction. It ensures reproducibility, transparency, and mathematical coherence, thereby facilitating seamless software integration.

5 Empirical Validation With Real-World Clinical Data

This section reports the empirical validation of the fuzzy logic–based patient satisfaction model using real-world clinical data, assessing its alignment with patient-reported experiences.

5.1 STUDY DESIGN AND PARTICIPANTS

The patient satisfaction survey was carried out in seven hospital departments, gynecology, dermatology, cardiology, medical emergency, ophthalmology, cancerology, gastroenterology, and ENT (Ear, Nose, and Throat), during routine clinical activity. These departments were deliberately selected to cover a broad spectrum of medical specialties, ensuring diversity in patient profiles, frequent direct contact between healthcare providers and patients, and a representative range of clinical situations relevant to satisfaction assessment.

Data were collected over a four-week period in 2025, encompassing both weekdays and weekends to reflect typical variations in hospital activity. Participation was open to adult patients aged 18 years and above who could understand the purpose of the study and provide informed consent. Patients in critical condition, those with severe cognitive impairment, or anyone unable to complete the questionnaire were excluded to ensure reliable self-reported responses.

In total, 80 adult patients took part in the survey on a voluntary basis. All participants were informed about the objectives of the study before providing consent, and their responses were recorded in complete anonymity to guarantee confidentiality and full adherence to ethical principles for research involving human subjects. The sample included 43 men (53.8%) and 37 women (46.2%), with ages ranging from 18 to 84 years (mean 36.7, SD 15.5). The departmental distribution was as follows: gynecology (18.8%), dermatology (17.5%), ENT (16.3%), medical emergency (12.5%), gastroenterology (10.0%), cancerology (7.5%), cardiology (6.3%), and ophthalmology (5.0%).

The dataset obtained from this survey provides a unique opportunity to compare patient-reported satisfaction scores with those generated by the fuzzy logic model, using the eight input dimensions described earlier in the study. This direct comparison forms the basis for the empirical validation presented in the following sections.

5.2 DATA COLLECTION AND PROCESSING

The evaluation covered eight key dimensions of patient satisfaction: communication and information, accessibility and reception, staff competence, environment and infrastructure, perceived care outcome, perception of cost and billing, patient involvement, and intention to return and recommend the facility. For each patient, two overall satisfaction scores were recorded: a self-declared score directly provided by the patient during the interview, and a score generated by the fuzzy logic system using the eight dimensions as inputs. All responses were collected in a structured questionnaire administered by trained staff, and numeric values were normalized to a 0–10 scale before integration into the fuzzy inference system.

The main descriptive statistics for the eight satisfaction dimensions and the two overall scores are presented in Table 3.

Table 3. Descriptive statistics of input dimensions and global scores

Variable	Sample Size (N)	Mean Score	Standard Deviation	Minimum Score	Median Score	Maximum Score
Communication and Information	80	6.88	1.76	2.0	7.0	10.0
Accessibility and Reception	80	5.85	1.99	2.0	6.0	10.0
Staff Competence	80	6.4	1.59	3.0	6.0	10.0
Environment and Infrastructure	80	5.9	1.83	2.0	6.0	10.0
Perceived Care Outcome	80	6.59	2.13	0.0	7.0	10.0
Cost and Billing Perception	80	6.25	1.45	3.0	6.0	10.0
Patient Involvement	80	6.18	1.85	3.0	6.0	10.0
Intention to Return and Recommend	80	5.96	1.94	2.0	6.0	10.0
Patient-Reported Satisfaction	80	5.75	2.00	1.0	6.0	10.0
Fuzzy-Generated Satisfaction	80	5.08	1.78	2.0	5.2	9.0

Descriptive analysis of the eight evaluated dimensions shows mean values ranging from 7.1 to 8.15 on a 0–10 scale, indicating generally high satisfaction levels reported by patients. Staff competence recorded the highest mean score, followed closely by intention to return and recommend, while perception of cost and billing showed the lowest mean and the highest standard deviation, reflecting greater variability in opinions on this aspect. The two global indicators, the fuzzy-generated score and the patient-reported score, presented similar averages (7.678 and 7.706 respectively), highlighting a general convergence between automated assessment and patients' subjective experience.

5.3 Comparative Analysis Of Satisfaction Scores

Descriptive statistics for the fuzzy-generated and patient-reported satisfaction scores are summarized in Table 4. These values provide an initial overview of the central tendencies and variability in both datasets before examining their distributional patterns.

Table 4. Descriptive statistics for fuzzy-generated and patient-reported satisfaction scores

	Fuzzy-Generated Satisfaction	Patient-Reported Satisfaction
Sample Size	80	80
Mean Score	5.08	5.74
Standard Deviation	1.78	2.00
Minimum Score	2.00	1.00
Median Score	5.18	6.00
Maximum Score	8.97	10.00

As presented in Table 4, the fuzzy generated scores are slightly lower on average compared with the patient reported scores, with respective means of 5.08 and 5.74. The standard deviation of the fuzzy generated results, which is 1.78, is also smaller than the 2.00 observed for the patient scores. This smaller dispersion suggests that the fuzzy system produces values that are less spread out, which indicates a tendency to moderate extreme evaluations.

To better understand these numerical differences, Figure 2 presents a visual comparison of the distributions through overlapping histograms. This representation provides a clear view of the central tendency and the spread of the two types of scores.

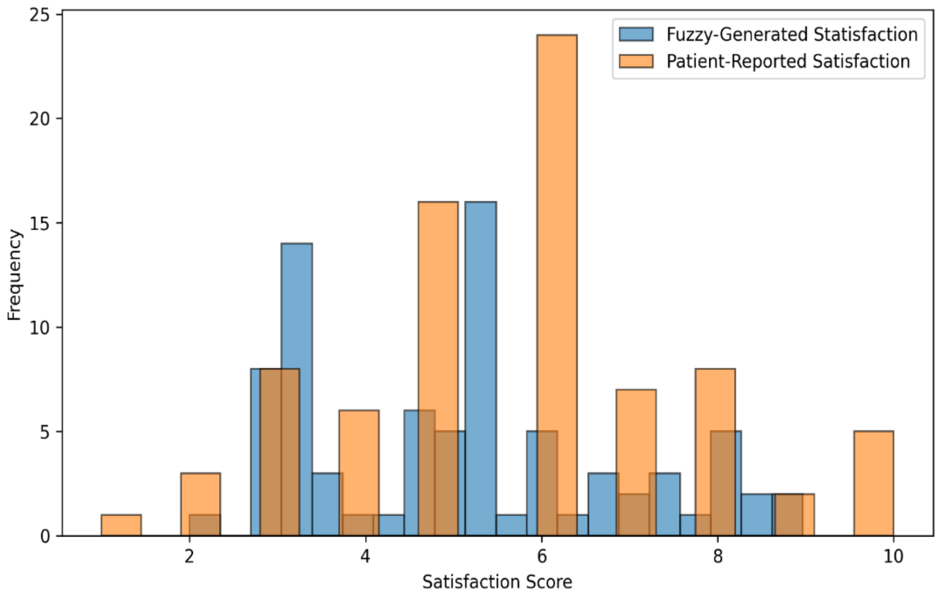

Fig. 2. Comparative histograms of fuzzy-generated and patient-reported satisfaction scores

The visual patterns reveal that the fuzzy generated scores are more tightly grouped around their mean, with fewer cases at the lowest and highest ends of the scale. In contrast, patient reported scores exhibit a wider spread, with a noticeable number of high ratings close to the maximum of 10. This behaviour indicates that the fuzzy logic approach, based on standardised evaluation criteria and balanced rule aggregation, generates results that are more stable and consistent. In comparison, patient reported scores are more likely to be influenced by personal perceptions, emotions, and situational factors.

5.4 Correlation, Error Metrics, And Interpretation

The relationship between fuzzy-generated and patient-reported satisfaction scores was examined using Pearson's correlation coefficient, the mean absolute error, and the root mean square error. The analysis revealed a strong and statistically significant positive correlation between the two sets of scores (Pearson $r = 0.76$, $p < 0.001$). On average, the difference between the two scoring methods was modest, with a mean absolute error of 1.12 and a root mean square error of 1.48, indicating that most predictions were close to the patient-reported values. The fuzzy system tended to underestimate satisfaction by approximately 0.66 points on a 0–10 scale. This tendency may be linked to the structured, criteria-based nature of the fuzzy inference system, which smooths extreme evaluations, and to patient-related factors such as individual interpretation of questionnaire items or the possible influence of healthcare staff during the reporting process.

Figure 3 visually illustrates this relationship, showing that most predictions cluster near the identity line, confirming the alignment between the two scoring approaches.

Fig. 3. Scatter plot of fuzzy-generated vs. patient-reported satisfaction scores

The observed agreement levels are consistent with, and in some cases exceed, those reported in similar fuzzy logic-based healthcare satisfaction assessment studies. A more detailed comparison with the literature is presented in the Discussion section.

5.5 Comparative Analysis With Conventional Methods

To better understand the value of the fuzzy logic system, its results were compared with three other approaches: a simple average of the eight satisfaction dimensions, a linear regression model, and a decision tree. Each method was evaluated against the patients' reported overall satisfaction using three indicators: Pearson's correlation (r), mean absolute error (MAE), and root mean square error (RMSE). The results are shown in Table 5.

Table 5. Comparative performance of different approaches in predicting overall satisfaction

Method	Pearson r	MAE	RMSE
Mean of 8 criteria	0.902	0.900	1.091
Linear Regression	0.950	0.488	0.619
Decision Tree	1.000	0.000	0.000
Fuzzy System (proposed)	0.760	1.127	1.480
Cross-validated (5-fold)	**Pearson r**	**MAE**	**RMSE**
Linear Regression	0.931	0.566	0.729
Decision Tree	0.837	0.775	1.151

The picture that emerges is clear. Linear regression provided the best balance between accuracy and stability: it maintained a strong correlation (r = 0.95 in-sample, r = 0.93 under cross-validation) while keeping errors relatively low. The decision tree, on the other hand, appeared perfect in-sample (r = 1.00, zero error), but its performance dropped substantially once cross-validation was applied, confirming that it had overfitted the training data. Even the simple average of the eight criteria performed surprisingly well, showing that patients' global satisfaction is closely aligned with the mean of their individual ratings.

Compared with these methods, the fuzzy system achieved lower predictive accuracy (r = 0.76). Yet, this result must be interpreted in context. The goal of the fuzzy framework is not only to maximize statistical performance but also to offer something the other models lack: transparency, interpretability, and adaptability to expert knowledge. Unlike regression coefficients or tree splits, fuzzy rules can be understood and adjusted by clinicians, making the system more trustworthy and easier to adapt to local cultural or institutional contexts.

In this sense, the fuzzy system should not be seen as competing with regression or machine learning, but rather as complementary. It brings interpretability where black-box models fall short, and it offers a way to capture linguistic nuances that numbers alone cannot express. Future research may even explore hybrid approaches that combine the accuracy of statistical models with the transparency of fuzzy logic.

5.6 Analysis Of Fuzzy Inference Surfaces

In order to gain deeper insight into the way the fuzzy logic system integrates different aspects of patient experience, four fuzzy inference surfaces were generated from the simulation dataset. Each surface provides a three-dimensional view of how two key variables interact to shape overall satisfaction. The variable pairs were selected as the most influential combinations based on both statistical results and expert assessment. Together, they encompass all eight input variables used in the model, ensuring that the analysis reflects its full decision-making scope.

Figure 4 (a) illustrates the relationship between Communication and Information, which had a mean score of 7.59, and Perceived Treatment Outcome, with a mean score of 7.79. When both variables receive ratings above 9, the predicted satisfaction approaches 9.8 out of 10. Conversely, if either variable fall below 5, satisfaction declines to about 5.5, even if the other remains high.

Figure 4 (b) examines the combination of Staff Competence, with a mean score of 8.15, and Patient Involvement and Personalized Care, averaging 7.71. High ratings in both dimensions yield satisfaction scores close to 9.7, while lowering either to around 5 reduces the predicted score to approximately 6.2. This underlines the importance of uniting strong clinical expertise with genuine personal engagement.

Figure 4 (c) explores the interplay between Cost and Billing Transparency, which averaged 7.13, and Intention to Return and Recommend, which averaged 7.99. The model predicts satisfaction levels above 9 when patients view financial processes as transparent and express strong loyalty. However, if transparency drops to 5 or lower, satisfaction decreases to around 6.0, even if loyalty remains high.

Figure 4 (d) shows the interaction between Reception and Accessibility, with a mean score of 7.65, and Environment and Infrastructure, averaging 7.73. Ratings above 9 in both factors produce satisfaction scores close to 9.6, while reducing either to 5 lowers the result to about 6.4. This confirms that first impressions and physical comfort play a decisive role in shaping patient perceptions.

Collectively, these four surfaces reveal how the fuzzy inference system produces gradual and interpretable variations in predicted satisfaction. They highlight that patient satisfaction is not driven by a single element but emerges from the combined effect of technical quality, interpersonal relationships, and environmental conditions. The findings suggest that the most effective improvement strategies are those that strengthen these factors together rather than focusing on them individually.

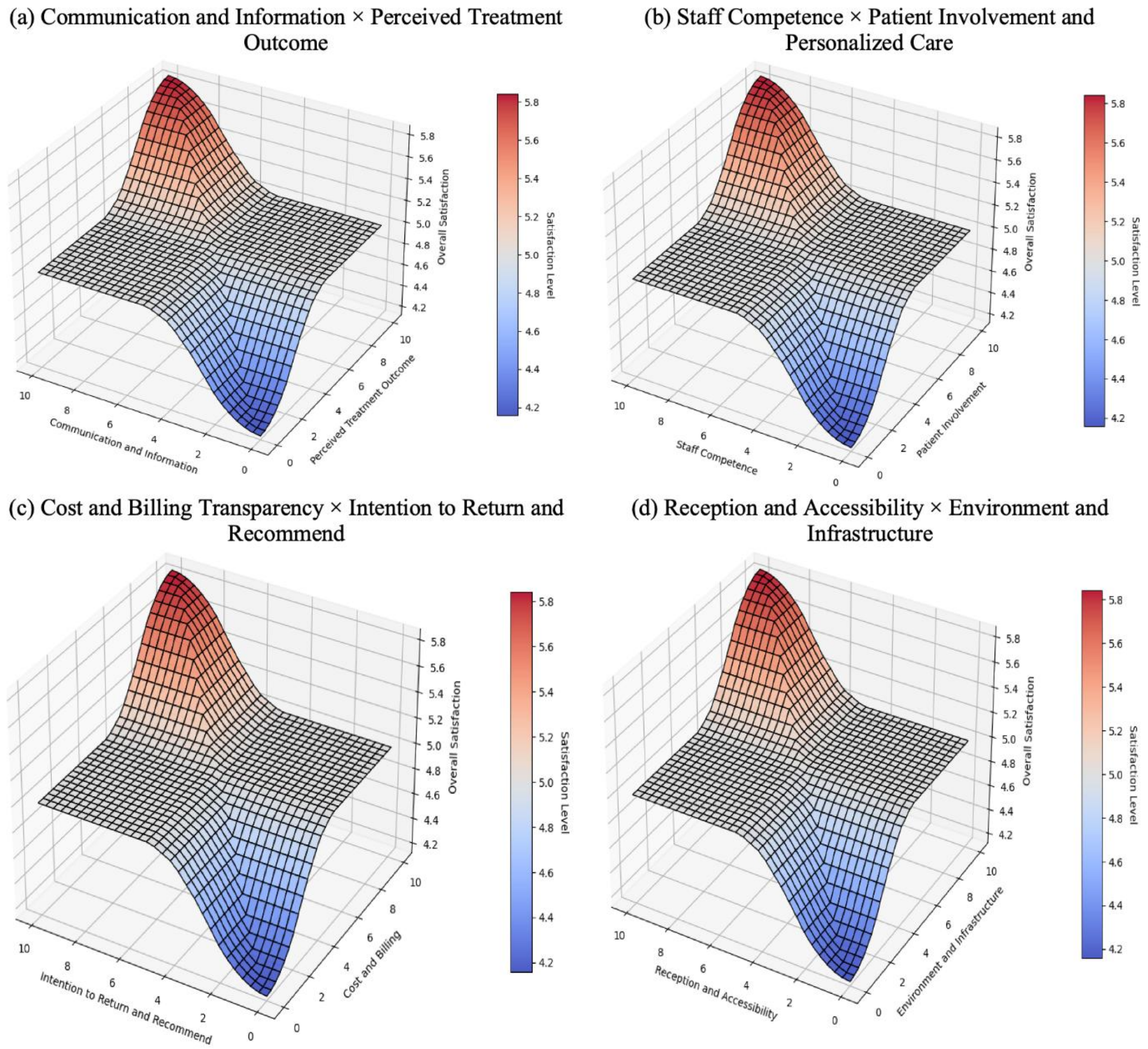

Fig. 4. ***Fuzzy inference surfaces showing the variation of fuzzy-generated satisfaction for four variable pairs encompassing all eight input variables***

6 DISCUSSION

This study presents an original, interpretable, and computationally efficient fuzzy logic framework for evaluating patient satisfaction in healthcare settings. Unlike many existing approaches that rely solely on simulated or survey-based data, the proposed system has been validated using real-world patient feedback collected from clinical practice. This empirical validation reinforces its practical relevance, ensuring that the generated satisfaction scores reflect authentic patient experiences rather than hypothetical scenarios. By integrating eight carefully selected dimensions, the framework delivers a rich and multidimensional representation of patient perceptions, addressing a crucial yet often under-measured aspect of healthcare quality.

6.1 Contributions To Patient Satisfaction Assessment

Conventional approaches to measuring satisfaction often depend on Likert-scale questionnaires or aggregated scores, which tend to oversimplify the complexity of patient perceptions [44]. The model developed in this study overcomes these limitations by applying fuzzy logic to transform subjective evaluations into mathematically coherent satisfaction scores. The use of real-world patient data in the validation process strengthens these contributions, as it demonstrates that the model can operate effectively in authentic clinical environments where responses are influenced by linguistic ambiguity, cultural diversity, and emotional subjectivity [56], [57]. One of its key advantages lies in its capacity to capture intermediate satisfaction levels, such as “moderately satisfied,” which are frequently lost in binary or ordinal scoring systems. This capability is particularly valuable for detecting incremental improvements in care quality and identifying the point at which interventions begin to positively influence patient perception. Although this study does not include a direct comparison with other techniques such as linear scoring systems or opaque machine learning models, the deliberate use of fuzzy logic aligns with the inherently subjective nature of patient satisfaction, preserving adaptability, interpretability, and cultural sensitivity.

6.2 Comparative Perspective And Originality Of The Proposed Approach

Beyond numerical performance, the strength of the proposed fuzzy logic framework lies in the way it captures the complexity of patient satisfaction. Whereas conventional surveys or regression models often reduce perceptions to linear or overly simplified scores, fuzzy logic can represent intermediate levels of satisfaction and account for non-linear interactions between different aspects of care. This allows for a more nuanced and realistic picture of patient experience.

Another distinctive element of this study is the type of data used. While many previous works rely on simulated or highly specific datasets, the present framework was validated on real patient-reported data collected across several hospital departments. This choice not only enhances the credibility of the results but also demonstrates the system’s ability to align algorithmic evaluations with lived experiences of care.

The model itself was designed with transparency and ease of use in mind. It is built on eight clearly defined dimensions and guided by membership functions and rules informed by both literature and expert knowledge. This makes the system adaptable to diverse institutional and cultural contexts without requiring extensive datasets or complex retraining. Its ability to generate outputs in just a few milliseconds also makes it suitable for seamless integration into hospital dashboards or patient feedback platforms.

Compared with hybrid approaches that combine fuzzy logic with machine learning, the proposed framework maintains a unique advantage in terms of explainability. While hybrid models can sometimes achieve higher predictive accuracy, they often do so at the cost of interpretability, which remains essential in healthcare contexts where decisions must be transparent and understandable.

Table 6 provides a synthetic overview of how the proposed framework positions itself among alternative approaches [17], [18], [21], [49], highlighting its balance between methodological rigor, empirical grounding, and practical applicability.

Table 6. Comparative Overview of Patient Satisfaction Assessment Approaches

Approach	Data Type	Ability to Handle Linguistic Uncertainty	Interpretability	Need for Large Training Dataset	Real-World Validation	Operational Feasibility	Notable Limitations
Likert-Scale Surveys	Patient-reported ordinal scores	✗	High (direct scores)	✗	✓	High	Oversimplifies nuanced perceptions; prone to ceiling effects
Classical Regression Models	Numerical variables	✗	Medium	✓	✓	Medium	Assumes linearity; limited handling of qualitative feedback
Fuzzy Logic with Simulated Data	Artificial datasets	✓	High	✗	✗	High	Lacks empirical grounding
Hybrid Fuzzy + Machine Learning	Real or large datasets	✓	Medium–Low	✓	✓	Medium–Low	Reduced interpretability
Proposed Fuzzy Logic Framework	Real patient data	✓	High	✗	✓	High	Slight underestimation of extreme values

By uniting methodological rigor with transparency and real-world validation, the proposed framework emerges as a distinctive and practical tool to enhance patient-centered quality assessment.

6.3 Interpretability And Trustworthiness

A defining strength of the proposed system lies in its interpretability, which is often missing from more complex predictive models. Each satisfaction score is produced through clearly defined rules and membership functions, enabling healthcare professionals to understand both the results and the underlying reasoning. In clinical environments, where decisions have direct consequences for patient well-being, such transparency is essential [41,58]. This interpretability fosters trust among clinicians and administrators, increasing the likelihood of adoption, especially when the system is adapted to local contexts. The integration of expert knowledge into the rule base ensures that the framework aligns with institutional realities and can be seamlessly adjusted to a wide variety of healthcare settings, from urban hospitals to rural clinics.

6.4 Operational Relevance And Strategic Deployment

From an operational perspective, the model offers significant advantages. Its evaluation time is under half a second, making it compatible with integration into hospital information systems, management dashboards, or patient feedback platforms. This speed facilitates continuous monitoring of perceived service quality and supports timely decision-making to enhance care delivery. The rule-based structure removes the dependency on large training datasets and reduces the workload associated with long surveys, while still providing actionable insights. Furthermore, the visual outputs generated by the system, such as satisfaction distribution curves and interaction surfaces, help decision-makers pinpoint areas requiring improvement in communication, infrastructure, or clinical procedures. The use of real patient feedback further enhances these operational benefits by ensuring that improvement strategies are grounded in actual patient experiences.

6.5 Limitations And Areas For Future Research

While this study demonstrates clear strengths, it is important to acknowledge certain limitations, without in any way undermining its validity or scientific relevance. The current validation relied on real patient data drawn from several hospital departments, including gynecology, dermatology, ENT (Ear, Nose and Throat), medical emergency, gastroenterology, cancerology, cardiology, and ophthalmology [10]. To further strengthen the robustness and generalizability of the model, future work should broaden this diversity by integrating data from other cultural settings and a wider range of clinical contexts [17]. Another limitation is that the fuzzy logic framework did not achieve the same level of predictive accuracy as purely statistical or machine learning models. However, this should not be viewed as a weakness. The true strength of fuzzy logic lies not in outperforming numerical models, but in offering interpretability, adaptability, and transparency, qualities that black-box methods often lack. Future research could explore hybrid approaches that combine the predictive power of statistical techniques with the clarity and usability of fuzzy logic, leveraging the strengths of both paradigms.

Because patient satisfaction is deeply shaped by cultural norms, expectations, and personal experiences, cross-cultural validation would make it possible to better capture the richness and variability of perceptions while adapting inference rules to reflect local realities [8]. Additionally, designing specialized model versions for specific patient groups, such as older adults, individuals with chronic illnesses, or those receiving palliative care, could lead to more precise and context-sensitive assessments [39].

Taken together, these perspectives open promising avenues for enhancing and refining this methodological framework while further consolidating its value as a practical tool for improving patient-centered care [16].

7 Conclusion And Future Work

This study introduced a fuzzy logic–based framework for evaluating patient satisfaction, validated with real data collected from several hospital departments. Grounded in eight well-defined dimensions and implemented through a Mamdani-type inference engine, the system translates subjective patient experiences into structured and interpretable satisfaction scores.

A key strength of this framework is its ability to deliver transparent and immediate results that capture the nuances of patient perception without oversimplification. By integrating linguistic variables, carefully designed membership functions, and a clear rule base, the model ensures both adaptability across diverse clinical settings and usability for healthcare professionals.

Its modular design makes it suitable for integration into hospital dashboards, feedback platforms, and quality monitoring systems. Tests with both simulated and real data demonstrated its ability to identify subtle variations in patient experience and provide actionable insights for service improvement.

Future work could include expanding the rule base through ongoing collaboration with healthcare experts, adopting adaptive learning mechanisms to reflect evolving patient expectations, and validating the system across different clinical contexts. Embedding the model into patient-facing digital tools and linking it with hospital information systems would further enhance its real-world applicability.

While statistical and machine learning models may sometimes achieve higher predictive accuracy, they often lack the transparency and interpretability that make fuzzy logic particularly valuable in healthcare. More than a computational tool, this framework serves as a decision-support system that provides clarity and trust where black-box models fall short.

By uniting interpretability, adaptability, and operational relevance, this fuzzy logic framework stands as a distinctive and scalable solution for patient-centered quality assessment, with the potential to play a central role in the next generation of intelligent healthcare systems.

Data and Code Availability

Due to privacy and ethical restrictions concerning patient data, the raw survey data used to validate the fuzzy subsystem are not publicly available. However, anonymized and aggregated data supporting the findings of this study are available from the corresponding author upon reasonable request. Requests will be evaluated in accordance with the ethical approval granted for this research and applicable data protection regulations.

REFERENCES

[1] Alemu, A.T., Bogale, E.K., Bogale, S.K., *al*.: Patient satisfaction and associated factors with inpatient health services at public hospitals in Ethiopia: a systematic review and meta-analysis. *BMC Health Serv Res* 24. (2024). https://doi.org/10.1186/s12913-024-11552-5.

[2] Boudreaux, E.D., Mandry, C.V., Wood, K.: Patient satisfaction data as a quality indicator: a tale of two emergency departments. *Acad Emerg Med*. (2003). https://doi.org/10.1111/j.1553-2712.2003.tb02000.x.

[3] Liu, L., Gauri, D.K., Jindal, R.P.: The Role of Patient Satisfaction in Hospitals' Medicare Reimbursements. *Journal of Public Policy & Marketing* (2021). https://doi.org/10.1177/0743915620984723.

[4] Hoffmann, O., Paul, F., Haase, R., Kern, R., Ziemssen, T.: Preferences, Adherence, and Satisfaction: Three Years of Treatment Experiences of People with Multiple Sclerosis. *Patient Preference and Adherence* (2024). https://doi.org/10.2147/PPA.S452849.

[5] Shoshanna Sofaer, Kirsten Firminger.: Patient perceptions of the quality of health services. *Annual Review of Public Health* (2005). https://doi.org/10.1146/annurev.publhealth.25.050503.153958.

[6] Priebe, S., Miglietta, E.: Assessment and determinants of patient satisfaction with mental health care. *World Psychiatry* (2019). https://doi.org/10.1002/wps.20586.

[7] Baker, D.L., Melnikow, J., Shoultz, J., Niederhauser, V., Diaz-Escamilla, R.: Translation of Health Surveys Using Mixed Methods. *Journal of Nursing Scholarship* (2010). https://doi.org/10.1111/j.1547-5069.2010.01368.x.

[8] Masino, C., Lam, T.C.M.: Choice of Rating Scale Labels: Implication for Minimizing Patient Satisfaction Response Ceiling Effect in Telemedicine Surveys. Telemedicine and e-Health (2014). https://doi.org/10.1089/tmj.2013.0350.

[9] Johnson, R.L., Saha, S., Arbelaez, J.J. *et al.*: Racial and ethnic differences in patient perceptions of bias and cultural competence in health care. *Journal of General Internal Medicine* (2004). https://doi.org/10.1111/j.1525-1497.2004.30262.x.

[10] Helena Vinagre, M. and Neves, J.: «The influence of service quality and patients' emotions on satisfaction», International Journal of Health Care Quality Assurance (2008). https://doi.org/10.1108/09526860810841183.

[11] Nottingham, Q. J., Johnson, D. M., & Russell, R. S.: The Effect of Waiting Time on Patient Perceptions of Care Quality. *Quality Management Journal* (2018). https://doi.org/10.1080/10686967.2018.1404368.

[12] Dunsch, F., K Evans, D., Macis, M., Wang, Q.: Bias in patient satisfaction surveys: a threat to measuring healthcare quality. *BMJ Global Health* (2018). https://doi.org/10.1136/bmjgh-2017-000694.

[13] Singh, A., & Prasher, A.: Measuring healthcare service quality from patients perspective: using Fuzzy AHP application. *Total Quality Management & Business Excellence* (2017). https://doi.org/10.1080/14783363.2017.1302794.

[14] Alkafaji, M. K., Al-Shamery, E. S.: A Fuzzy Assessment Model for Hospitals Services Quality based on Patient Experience. *Karbala International Journal of Modern Science* (2020). https://doi.org/10.33640/2405-609X.1734.

[15] Gupta, K., Kumar, P., Upadhyaya, S., Poriye, M., Aggarwal, S.: Fuzzy logic and machine learning integration: Enhancing healthcare decision-making. *International Journal of Computer Information Systems and Industrial Management Applications*. 16 (3), 20-20 (2024).

[16] Mularczyk-Tomczewska, P., Gujski, M., Koperdowska, J.M., Wójcik, J., Silczuk, A.: Factors Influencing Patient Satisfaction with Healthcare Services in Poland. *Med Sci Monit* (2025). https://doi.org/10.12659/MSM.948225.

[17] Ferreira, D. C., Vieira, I., Pedro, M. I., Caldas, P., Varela, M. (2023). Patient Satisfaction with Healthcare Services and the Techniques Used for its Assessment: A Systematic Literature Review and a Bibliometric Analysis. *Healthcare* (2023). https://doi.org/10.3390/healthcare11050639.

[18] Parasuraman, A., Zeithaml, V.A., Berry, L. L.: Servqual: A multiple-item scale for measuring consumer perc. *Journal of Retailing*. 64, 12–40 (1988).

[19] Doyle, C., Lennox, L., & Bell, D.: A systematic review of evidence on the links between patient experience and clinical safety and effectiveness. *BMJ Open* (2013). https://doi.org/10.1136/bmjopen-2012-001570.

[20] Donabedian, A.: The quality of care: how can it be assessed?. *Jama* (1988). https://doi.org/10.1001/jama.1988.03410120089033.

[21] Dagger, T. S., Sweeney, J. C., Johnson, L. W.: A hierarchical model of health service quality: scale development and investigation of an integrated model. *Journal of service research* (2007). https://doi.org/10.1177/1094670507309594.

[22] Otani, K., Waterman, B., Faulkner, K.M., Boslaugh, S., Burroughs, T.E., Dunagan, C. W.: Patient satisfaction: focusing on excellent. *Journal of healthcare management*. 54, 93-102 (2009).

[23] Suzuki, A., Negishi, E.: Fuzzy Logic Systems for Healthcare Applications. *Journal of Biomedical and Sustainable Healthcare Applications* (2024). https://doi.org/10.53759/0088/JBSHA20240401.

[24] Leite, C.R., Sizilio, G.R., Neto, A.D., Guerreiro, A. M.: A fuzzy model for processing and monitoring vital signs in ICU patients. *BioMed Eng OnLine* (2011). https://doi.org/10.1186/1475-925X-10-68.

[25] Peleg, M., Tu, S.: Decision support, knowledge representation and management: Decision support, knowledge representation and management in medicine. *Yearbook of medical informatics* (2006). https://doi.org/10.1055/s-0038-1638482.

[26] Shakshuki, E., Reid, M.: Multi-Agent System Applications in Healthcare: Current Technology and Future Roadmap. *Procedia Computer Science* (2015). https://doi.org/10.1016/j.procs.2015.05.071

[27] Geman, O., Turcu, C. O., Graur, A.: Parkinson's disease assessment using fuzzy expert system and nonlinear dynamics. Advances in Electrical and Computer Engineering. 13, 41-46 (2013).

[28] Ianculescu, M., Constantin, V. Ș., Gușatu, A. M., Petrache, M. C., Mihăescu, A. G., Bica, O., Alexandru, A.: Enhancing connected health ecosystems through IoT-enabled monitoring technologies: A case study of the monit4healthy system. *Sensors* (2025). https://doi.org/10.3390/s25072292.

[29] Zadeh, L. A.: Fuzzy sets. *Information and Control* (1965). https://doi.org/10.1016/S0019-9958 (65) 90241-X.

[30] Bellman, R. E., Zadeh, L. A.: Decision-making in a fuzzy environment. *Management Science* (1970). https://doi.org/10.1287/mnsc.17.4.B141.

[31] Morente-Molinera, J. A., Pérez, I. J., Ureña, M. R., Herrera-Viedma, E.: On multi-granular fuzzy linguistic modeling in group decision making problems: A systematic review and future trends. *Knowledge-Based Systems* (2015). https://doi.org/10.1016/j.knosys.2014.11.001

[32] Djam, X. Y., Kimbi, Y. H.: A fuzzy expert system for malaria management. *Artificial Intelligence in Medicine*. 52, 1–9 (2011).

[33] Yao, W., Kumar, A.: CONFlexFlow: integrating flexible clinical pathways into clinical decision support systems using context and rules. *Decision Support Systems* (2013). https://doi.org/10.1016/j.dss.2012.10.008

[34] Cui, H., Tan, Q.: A fuzzy decision support system for medical service quality management in hospitals. *Int J Comput Intell Syst* 18, 57 (2025). https://doi.org/10.1007/s44196-025-00773-z.

[35] Ortiz Barrios, M., et al.: A fuzzy hybrid MCDM approach for assessing healthcare services. *Sci Rep* 13, 4591 (2023). https://doi.org/10.3390/ijerph20054591.

[36] Neto, A.B.L., Andrade, J.P.B., Loureiro, T.C.J., de Campos, G.A.L., Fernandez, M.P.: A Multi-agent System Using Fuzzy Logic Applied to eHealth. In: Novais, P., *et al.* Ambient Intelligence – Software and Applications –, 9th International Symposium on Ambient Intelligence. ISAmI2018 2018. Advances in Intelligent Systems and Computing (2019). https://doi.org/10.1007/978-3-030-01746-0_25.

[37] Hernandez-Leal, F., Alanis, A., Patiño, E., Jimenez, S.: Multiagent Emergency Triage Classification System for Health Monitoring. In: Jezic, G., Chen-Burger, J., Kusek, M., Sperka, R., Howlett, R.J., Jain, L.C. (eds) Agents and Multi-Agent Systems: Technologies and Applications 2021. Smart Innovation, Systems and Technologies (2021). https://doi.org/10.1007/978-981-16-2994-5_30.

[38] Jayalakshmi, M., Garg, L., Maharajan, K., Jayakumar, K., Srinivasan, K., Bashir, A. K., Ramesh, K.: Fuzzy logic-based health monitoring system for COVID'19 patients. *Computers, Materials and Continua,* (2021). https://doi.org/10.32604/cmc.2021.015352.

[39] Abdalla, A. Y., Abdalla T. Y., Chyaid, A. M.: «Internet of Things-Based Fuzzy Systems for Medical Applications: A Review,» in *IEEE Access* (2024). https://doi.org/10.1109/ACCESS.2024.3487812.

[40] Tkachenko, R., Kovalyshyn, O.: A method of assessing of clinic patients feedback with fuzzy logic. *Bulletin of Lviv State University of Life Safety*. https://journal.ldubgd.edu.ua/index.php/Visnuk/article/view/141 (2018).

[41] Amann, J., Blasimme, A., Vayena, E., Frey, D., Madai, V. I.: Explainability for Artificial Intelligence in Healthcare: A Multidisciplinary Perspective. *BMC Medical Informatics and Decision Making* (2022). https://doi.org/10.1186/s12911-020-01332-6.

[42] Chen, T., Shang, C., Su, P., Keravnou-Papailiou, E., Zhao, Y., Antoniou, G., Shen, Q.: A decision tree-initialised neuro-fuzzy approach for clinical decision support. *Artificial Intelligence in Medicine* (2021). https://doi.org/10.1016/j.artmed.2020.101986.

[43] Herrera, F., Verdegay, J. L.: Linguistic assessments in group decision making. *Fuzzy Sets and Systems*. 88, 49–58 (1997).

[44] Oluwagbemi OO, Oluwagbemi FE, Jatto A, Hui C. MAVSCOT: A fuzzy logic-based HIV diagnostic system with indigenous multi-lingual interfaces for rural Africa. PLoS One. 2020 Nov 6; 15 (11): e0241864. doi: 10.1371/journal.pone.0241864. PMID: 33156877; PMCID: PMC7647102.

[45] Golmohammadi, D., Zhao, L., Dreyfus, D.: Using machine learning techniques to reduce uncertainty for outpatient appointment scheduling practices in outpatient clinics. *Omega* 120, 102907 (2023). https://doi.org/10.1016/j.omega.2023.102907.

[46] Improta, G., Mazzella, V., Vecchione, D., Santini, S., Triassi, M.: Fuzzy logic-based clinical decision support system for the evaluation of renal function in post-transplant patients. *J Eval Clin Pract* 26 (4), 1224–1234 (2020). https://doi.org/10.1111/jep.13302.

[47] Siddique, N., Adeli, H.: Computational intelligence: synergies of fuzzy logic, neural networks and evolutionary computing. John Wiley & Sons (2013).

[48] Purandhar, N., Ayyasamy, S., Saravana Kumar, N.M.: Strategic real time framework for healthcare using fuzzy C-means systems. *Autom Softw Eng* (2022). https://doi.org/10.1007/s10515-021-00302-048.
[49] Endeshaw, B.: Healthcare service quality-measurement models: a review. *Journal of Health Research,* (2021). https://doi.org/10.1108/JHR-07-2019-0152.
[50] Demir, M. O., Basaran, M. A., Simonetti, B.: Determining factors affecting healthcare service satisfaction utilizing fuzzy rule-based systems. *Journal of Applied Statistics* (2016). https://doi.org/10.1080/02664763.2016.1181727.
[51] Bouchon-Meunier, B., Marsala, C.: Fuzzy logic, principles, decision support. *Hermès - Lavoisier*. (2003).
[52] Arboleda A. M.: Reprint of: Satisfaction with life and perception of healthcare services. *International Journal of Hospitality Management* (2023). https://doi.org/10.1016/j.ijhm.2023.103516.
[53] Magdalena, L.: Fuzzy Rule-Based Systems. In: Kacprzyk, J., Pedrycz, W. (eds) Springer Handbook of Computational Intelligence. Springer Handbooks. Springer, Berlin, Heidelberg (2015). https://doi.org/10.1007/978-3-662-43505-2_13.
[54] Pedrycz, W.: Fuzzy modelling: paradigms and practice. Springer Science & Business Media (1996).
[55] Salinas, M., Velandia, D., Mayeta-Revilla, L., Bertini, A., Querales, M., Pardo, F., Salas, R.: An Explainable Fuzzy Framework for Assessing Preeclampsia Classification. Biomedicines, (2025). https://doi.org/10.3390/biomedicines13061483.
[56] Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information Sciences,* 8 (3), 199–249. https://doi.org/10.1016/0020-0255 (75) 90036-5.
[57] Asghar, M. Z., Ullah, I., Shamshirband, S., Kundi, F. M., Habib, A.: Fuzzy-Based Sentiment Analysis System for Analyzing Student Feedback and Satisfaction. Preprints (2019).
[58] https://doi.org/10.20944/preprints201907.0006.v1.
[59] Fukami, T.: Enhancing Healthcare Accountability for Administrators: Fostering Transparency for Patient Safety and Quality Enhancement. *Cureus* 2024. https://doi.org/10.7759/cureus.66007.