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RESEARCH ARTICLE

EVALUATING PATIENT SATISFACTION THROUGH A FUZZY LOGIC FRAMEWORK BASED ON SIMULATED PROFILES

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Abstract

Measuring patient satisfaction remains a major challenge in healthcare, as it involves perceptions that are often subjective, multidimensional, and expressed in vague or imprecise terms.This study introduces a fuzz y logic framework designed to model the complexity of patient experie nce using linguistic variables and transparent reasoning rules.In the abs ence of real-world data, which are currently being collected through a clinical questionnaire, the system is tested on a set of simulated patient profiles. Eight key dimensions of satisfaction are considered, including communication, accessibility, staff competence, perceived outcomes, and infrastructure. Each criterion is represented by tailored membership functions, and a Mamdani inference mechanism produces an overall satisfaction score ranging from 0 to 10. A synthetic dataset of fifty patient profiles was generated based on expected distributions, allowing for an initial assessment of the system's consistency and relevance. The results suggest that the model provides meaningful and interpretable outputs,offering a promising tool for future integration into healthcare quality monitoring platforms. This simulation-based study serves as a preparatory step before empirical deployment and highlights the flexibi lity of fuzzy logic in capturing the nuances of patient perception.

Introduction:-

Improving the quality of healthcare services remains a global priority, particularly as systems strive to align clinical excellence with patient-centered care. In this context, patient satisfaction has emerged as a key performance indicator, directly influencing health outcomes, service utilization and policy decisions [1, 2, 3]. Beyond its evaluative function, satisfaction reflects the patient's subjective perception of the care experience, encompassing relational, organizational and environmental dimensions [4, 5, 6]

Numerous studies have demonstrated that high satisfaction levels are positively associated with increased adherence to treatment, improved trust in health institutions and even better clinical recovery trajectories [7, 8]. Yet, accurately

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capturing patient satisfaction remains a complex task. Subject to cognitive biases, cultural variability and survey design limitations, traditional measurement instruments sometimes fall short in representing the nuanced realities of healthcare experiences [9,10].

To address these limitations, researchers have explored computational approaches capable of modeling subjective evaluations with greater flexibility. Among them, fuzzy logic has garnered attention for its ability to formalize imprecise concepts and reason with uncertainty [11]. These two features are essential for representing human perception [12, 13]. By incorporating fuzzy sets and linguistic rules, such systems offer a promising framework for evaluating patient satisfaction in a more adaptive and personalized manner [14] [15].

Despite this potential, the deployment of fuzzy systems for patient satisfaction assessment remains relatively limited and mostly experimental [16]. Moreover, few studies have validated these models using simulated patient profiles prior to real-world data collection. However, this intermediate step is critical for evaluating the internal coherence and behavior of the model across a variety of hypothetical satisfaction scenarios [17].

This article addresses this gap by proposing and validating a fuzzy inference system designed to assess patient satisfaction based on simulated healthcare experiences. The objective is to ensure the robustness of the model before its deployment on real patient data, which are currently being collected through a clinical questionnaire. Through this preparatory phase, we aim to demonstrate the interpretability, responsiveness and internal consistency of the system across diverse patient profiles. Ultimately, this study contributes to the methodological rigor of satisfaction evaluation tools and prepares the ground for future empirical validation.

To tackle these challenges, we introduce a fuzzy logic-based model specifically designed to assess patient satisfaction across eight essential dimensions. The paper begins in Section 2 by presenting the conceptual underpinnings of patient satisfaction and explaining why fuzzy logic is particularly well-suited to this task. Section 3 explores related work and situates our contribution within the existing body of research. Sections 4 and 5 describe our methodological framework and detail how the model was built—from selecting variables to defining fuzzy rules and designing the simulation. Section 6 shares the results of the simulation, highlighting key patterns and insights. Section 7 then discusses the implications of our findings, examines the model's limitations, and outlines potential areas for future work. Finally, Section 8 concludes the paper by summarizing the main contributions and pointing toward practical applications.

Background and Motivation:-

Assessing patient satisfaction remains one of the most intricate tasks in healthcare quality evaluation. Unlike measurable clinical indicators, satisfaction reflects how patients perceive their experience. These perceptions are shaped by personal expectations, cultural norms, emotions, and subtle interactions with healthcare staff [18]. Often, patients express their experiences using subjective or imprecise terms, which are difficult to capture with rigid numerical scales or binary classifications [19, 20, 21].

Fuzzy logic provides a compelling approach to address this complexity. As a mathematical framework capable of handling vagueness and uncertainty [22], it allows for reasoning with linguistic expressions such as "moderate", "very satisfied", or "somewhat acceptable" [23, 24]. Instead of forcing patient feedback into sharply defined categories, fuzzy logic accommodates gradual nuances. This feature makes it especially suitable for modeling satisfaction, where important meanings often reside in ambiguity rather than in binary distinctions [25].

In the present study, we propose a fuzzy inference system structured around eight essential dimensions of satisfaction. Each of these dimensions, including communication, accessibility, staff competence, and perceived outcomes, is translated into mathematical functions that reflect how patients commonly describe their experiences. These variables are processed through a set of fuzzy rules to compute a global satisfaction score.

Although a structured questionnaire has already been designed for future data collection, the empirical phase has not yet begun. To anticipate this, we simulate synthetic patient profiles based on plausible response patterns. This strategy allows us to test the consistency and behavior of the system across a broad range of hypothetical cases [26, 27].

This simulation phase is a critical step in the development process. It provides an opportunity to refine the system, evaluate its interpretability, and ensure that the outputs remain meaningful and reliable in the absence of real data. By validating the model in this way, we lay a solid foundation for its eventual deployment in real clinical environments [28, 29] [30].

Related Work:-

Patient satisfaction has gradually become a cornerstone of healthcare quality research, as numerous studies have established its close link with clinical outcomes, treatment adherence and institutional trust [1, 2]. Donabedian's foundational model placed patient perception at the heart of healthcare evaluation [3], and subsequent empirical work confirmed its role in reinforcing patient engagement and confidence in the health system [7, 5].

However, the process of measuring satisfaction remains fraught with methodological difficulties. Cultural differences, emotional states and linguistic subtleties all influence how patients respond to surveys. These factors often introduce bias and limit the generalizability of results [19, 31]. In addition, standard instruments using fixed rating scales tend to overlook the nuances embedded in subjective assessments, particularly when experiences are expressed in approximate or emotionally charged terms [9, 10]. Faced with these limitations, researchers have turned to computational models better equipped to handle ambiguity and vagueness.

Fuzzy logic has emerged as a promising approach in this regard. Its capacity to formalize imprecise language and reason with gradations of meaning makes it particularly well suited to capturing the complexity of patient expression [23, 12]. Zadeh's work on fuzzy sets, and his extension to decision-making under uncertainty, laid the theoretical foundation for this methodology [12,13]. More recent studies have applied these principles to healthcare contexts, where fuzzy systems have been used to convert qualitative judgments into interpretable outputs that reflect the variability of human perception [24, 25].

Several authors have explored the use of fuzzy logic specifically for evaluating healthcare service quality. Alkafaji and Al-Shamery proposed a model based on patients' lived experiences to measure perceived quality in hospitals [14]. In a different context, Suzuki and Negishi investigated the integration of fuzzy logic into real-time satisfaction monitoring within clinical environments [16]. These approaches demonstrate the potential of fuzzy reasoning to address the complexity of subjective evaluations, especially when patients use vague descriptors such as ―acceptable‖ or ―almost good‖ to express their views.

Other researchers have sought to combine fuzzy systems with multi-agent architectures to improve adaptability and decentralization in health decision-making. Neto and colleagues developed a multi-agent eHealth system with fuzzy logic at its core, allowing for distributed assessment of patient states [27]. Similarly, Hernandez-Leal et al. applied agent-based logic to emergency triage, demonstrating that combining autonomous reasoning with fuzzy rules could improve responsiveness in high-pressure environments [32].

One recurrent limitation in many existing models is the absence of a preparatory validation phase prior to the use of real clinical data. This step is crucial to ensure the reliability and coherence of fuzzy systems when faced with diverse patient profiles. Salinas and collaborators addressed this issue by testing a fuzzy framework through simulated clinical cases to evaluate classification accuracy and internal consistency [33]. Along similar lines, Chen et al. introduced a hybrid neuro-fuzzy model optimized using decision trees, highlighting the relevance of simulation in strengthening interpretability and performance under uncertainty [29].

In light of this background, the present study distinguishes itself by responding to two unmet needs in the literature. First, it introduces a fuzzy inference system specifically structured around carefully selected satisfaction dimensions drawn from clinical and experiential considerations. Second, it undertakes a simulation-based validation using synthetic patient profiles before any real data are introduced. This strategy enables the early detection of inconsistencies and enhances the robustness of the system, while offering a transparent and reproducible framework for future deployment in healthcare environments.

Methodology:-

This section outlines the methodological foundations of the fuzzy satisfaction evaluation system. In light of the unavailability of real-world patient feedback at this stage, we opted for a simulation-based approach to assess the internal coherence and sensitivity of the model. This strategy was grounded in a previously designed clinical questionnaire, thereby ensuring semantic alignment between simulated profiles and the model's fuzzy variables. Our methodological choices are aligned with established practices in early-phase AI validation when access to empirical data is limited [9, 16].

Simulation-Based Approach:
Rather than delaying the validation of the fuzzy system, we simulated synthetic patient cases to explore how the model interprets diverse scenarios. The decision to generate artificial data is consistent with prior studies that emphasize the value of simulation in preclinical validation stages, particularly for fuzzy or rule-based systems where logical interpretability is central [34] [35].

We constructed a dataset comprising 100 synthetic patient profiles, covering a continuum of experiences from highly positive to strongly negative. The design aimed to test the system's responsiveness in both well-defined and borderline cases, especially those that present ambiguity in the perceived quality of care. This approach allowed us to observe how small variations in inputs such as minor shifts in perceived communication or environment quality translate into changes in the overall satisfaction score.

To enhance the realism of the simulated data, coherence constraints were introduced. For example, a profile with poor communication could not be paired with an extremely high level of patient involvement or perceived outcome. This form of expert-driven validation is a known method to ensure the plausibility of synthetic datasets when real data are not yet available [36].

Each of the eight input criteria was varied independently and jointly across profiles, avoiding skewed distributions and allowing us to fully explore the multidimensional input space of the fuzzy system. This controlled variation ensured that the inference engine was tested under a broad range of plausible healthcare experiences.

Questionnaire Design as Simulation Framework:
The structure and semantics of the simulated profiles were not arbitrary. They were derived from a clinical questionnaire previously developed as part of this research. Although the questionnaire has not yet been administered in a healthcare setting, it was designed according to validated instruments in the literature for measuring patient experience and satisfaction [8, 37].

The questionnaire includes eight key dimensions such as communication and information, competence of medical staff, environment and infrastructure, and perception of care results. These same dimensions were encoded as fuzzy input variables in the system. For instance, the communication variable aggregates indicators such as clarity of explanations, frequency of updates, and responsiveness to patient concerns.

Linguistic labels used in the fuzzy logic engine such as "poor", "average" and "excellent" were directly inspired by the Likert-type response options in the questionnaire [38]. This semantic continuity ensures that future real patient responses can be interpreted by the system without requiring structural changes to the model. The alignment between survey design and fuzzy modeling has been highlighted in several works as a key factor in ensuring interoperability and interpretability of AI systems in healthcare contexts [19, 3].

Technical Tools:
The fuzzy inference system was developed in Python using the scikit-fuzzy library. This open-source framework offers robust tools for defining fuzzy sets, implementing rule bases, and managing inference pipelines. The model's architecture was modular, with dedicated components for fuzzification, rule evaluation, aggregation, and defuzzification [39].

To support the simulation phase, Python scripts were developed to automatically generate synthetic patient profiles, assign fuzzy membership values, and calculate satisfaction scores. These scripts were designed to handle batch processing, enabling the simulation of multiple profiles under various test conditions.

The outcomes were visualized through graphical representations such as membership function plots, satisfaction distribution histograms, and 3D inference surfaces. These visual outputs were exported in vector and raster formats to facilitate future inclusion in clinical dashboards, monitoring tools, or decision-support environments. Such visual validation is frequently employed in fuzzy logic applications to provide intuitive feedback to both developers and clinical stakeholders [20, 13] [40].

Fuzzy Satisfaction Model Design:-

Fuzzy logic offers a robust and interpretable framework for modeling subjective perceptions, particularly well suited to the evaluation of patient satisfaction. Unlike rigid numerical systems, fuzzy models handle imprecision and ambiguity naturally, enabling more nuanced assessments of individual experiences [37], [26] [41].

This section presents the structure and rationale of the fuzzy system designed for this study, covering the linguistic variables, membership functions, rule base, and inference process [42].

Input and Output Variables:

Eight input variables were selected based on well-established dimensions of patient satisfaction found in healthcare quality literature and prior fuzzy applications [14], [37], [43]. A single fuzzy output variable captures the overall satisfaction score. All variables were normalized to the [0–10] interval to standardize interpretation and ensure consistency during fuzzification and aggregation [44], [26].

Table 1:-Linguistic Variables Used in the Fuzzy Mode

No.	Variable Name	Type	Universe of Discourse	Description
1	Communication and Information	Input	[0 – 10]	Clarity, responsiveness, and active listening
2	Reception and Accessibility	Input	[0 – 10]	Ease of admission, waiting time, and accessibility
3	Staff Competence	Input	[0 – 10]	Professionalism, empathy, and technical expertise
4	Environment and Infrastructure	Input	[0 – 10]	Comfort, hygiene, and space organization
5	Perceived Treatment Outcome	Input	[0 – 10]	Effectiveness of care from the patient's point of view
6	Cost and Billing Transparency	Input	[0 – 10]	Affordability and clarity of financial information
7	Patient Involvement and Personalized Care	Input	[0 – 10]	Degree of participation and care customization
8	Intention to Return and Recommend	Input	[0 – 10]	Loyalty and likelihood of recommendation
9	Overall Satisfaction	Output	[0 – 10]	Aggregated perception of satisfaction level

This configuration enables a balanced evaluation of service quality across interpersonal, environmental, and institutional dimensions [14], [44].

Membership Functions:
For each input variable, appropriate membership functions were defined to map linguistic terms (e.g., low, medium, high) into fuzzy sets. Triangular and trapezoidal shapes were selected for most criteria due to their simplicity and interpretability [44], [27]. Gaussian curves were adopted where a centered, symmetric evaluation was preferred, particularly for ―Staff Competence‖ [25].

Figure 1 presents the membership functions associated with the eight input variables used in the fuzzy evaluation system. These functions translate patient perceptions into linguistic categories, allowing for a nuanced interpretation of aspects such as communication, accessibility, treatment effectiveness, and billing clarity.

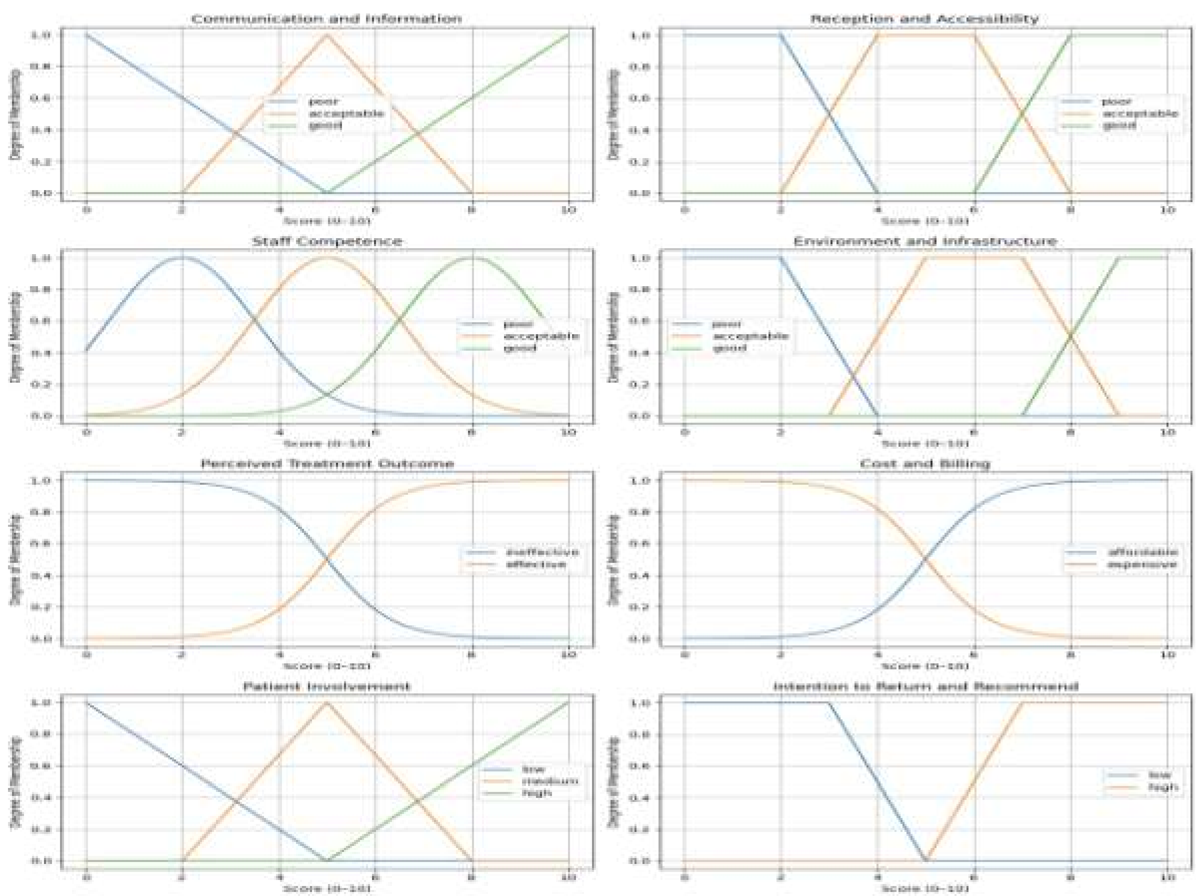

Figure 1:- Membership functions of the eight input variables in the fuzzy satisfaction evaluation system

Figure 2 illustrates the membership functions defined for the output variable, Overall Satisfaction. This variable synthesizes the patient's global evaluation of care on a scale from 0 to 10, integrating all relevant input dimensions. The fuzzy formulation of this output enables a more flexible and interpretable representation of satisfaction levels.

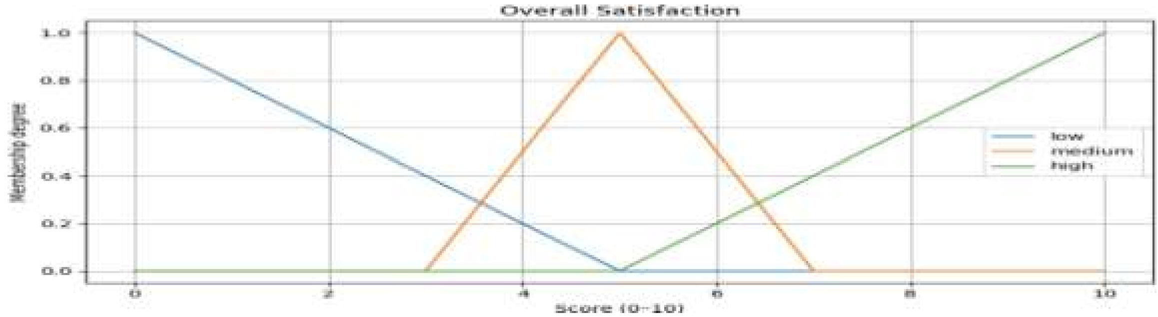

Figure 1:- Fuzzy membership functions defining the output variable "Overall Satisfaction"

All membership functions were implemented using scikit-fuzzy in Python, allowing seamless fuzzification during simulation [28].

Rule Base Construction:

The fuzzy rule base consists of 20 manually designed rules that reflect common clinical scenarios and expert reasoning. These rules were inspired by classical models of care quality, notably those of Donabedian and Parasuraman et al. [23], [3], and adapted to fuzzy inference contexts following guidance from Bouchon-Meunier and others [43]. Table 2 provides illustrative examples of fuzzy inference rules used to compute patient satisfaction. Each rule combines input variables such as Communication and Information, Perceived Treatment Outcome, Reception and Accessibility, Cost and Billing, Patient Involvement, and Intention to Return to infer a global satisfaction level. These rules reflect typical clinical situations and support transparent and interpretable decision-making within the fuzzy system.

Table 2:- Examples of Fuzzy Inference Rules

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

These rules were carefully reviewed to ensure they made sense both individually and as a whole. Particular attention was paid to their ability to reflect realistic clinical situations and to provide coherent guidance across different patient satisfaction scenarios. Their design was informed by established frameworks in healthcare quality and fuzzy logic decision-making [14], [3], [43].

Inference Process and Mathematical Modeling:

A Mamdani-type inference engine was used for its interpretability and alignment with linguistic reasoning in healthcare [37], [25]. The inference process follows four sequential steps. This approach ensures semantic transparency and robustness, supporting explainability for clinical stakeholders [44], [37].

Step 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:

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

Step 2: Evaluation of Fuzzy Rules
A fuzzy rule can be intuitively expressed as:

$$R_k : \text{IF } x_1 \text{ is } A_1^k \text{ AND } x_2 \text{ is } A_2^k \text{ AND } \dots \text{ AND } x_n \text{ is } A_n^k, \text{THEN } y \text{ is } B^K \quad (2)$$

Formally, for any number of inputs:

$$R_k : \text{IF } \bigwedge_{i=1}^{n} (x_i \text{ is } A_i^k) \text{ THEN } y \text{ is } B^k \quad (3)$$

The activation degree α_K of rule R_k is given by :

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

Step 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.
Step 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.

Simulation results:-

Improving the quality of healthcare services remains a global priority, particularly as systems strive to align clinical excellence with patient-centered care. In this context, patient satisfaction has emerged as a key performance indicator, directly influencing health outcomes, service utilization and policy decisions [1, 2, 3]. Beyond its evaluative function, satisfaction reflects the patient's subjective perception of the care experience, encompassing relational, organizational and environmental dimensions [4, 5, 6]

In this section, we explore the outcomes generated by the simulation of our fuzzy satisfaction model. We start by discussing the relevance and credibility of the simulated dataset, then move on to analyze how the model behaves across different patient profiles and score distributions, providing insight into its interpretability and consistency.

Credibility and Realism of the Simulated Data set:

To assess the fuzzy satisfaction system in a way that balances control and realism, a dataset comprising 100 synthetic patient profiles was created. Each profile integrates plausible combinations of key satisfaction determinants, including Communication and Information, Reception and Accessibility, Staff Competence, Environment and Infrastructure, Treatment Outcome, Cost and Billing, Patient Involvement, and Intention to Return. These criteria reflect core dimensions frequently explored in healthcare satisfaction research [1], [5], [21].
The values assigned to each dimension were carefully sampled to mirror the natural variability typically observed in real-world patient feedback. For instance, dimensions such as staff competence and infrastructure often yield high ratings in hospital surveys, whereas aspects related to communication or cost tend to show greater heterogeneity [4], [5], [21]. These known patterns were deliberately incorporated into the simulation to ensure ecological validity and relevance.

While patients commonly express their satisfaction using integers on a Likert scale, the outputs generated by the fuzzy inference system are continuous real-valued scores. This is a direct result of how fuzzy systems operate. Membership functions translate crisp integer inputs into overlapping fuzzy sets, and the defuzzification process then yields continuous satisfaction scores [12], [13]. Rather than undermining realism, this continuous modeling enhances it, allowing the system to capture subtle differences in patient profiles that would be lost in a strictly categorical framework.

This approach brings important analytical advantages. It enables a fine-grained evaluation of the system's logic and reveals how well the rule base responds to nuanced input patterns. Furthermore, by using real-valued inputs during simulation, we can better examine the system's coherence, sensitivity, and smoothness—key attributes for ensuring reliable decision support in complex clinical environments [14], [12].

The use of simulated patients in this context is consistent with established methodologies in health informatics. Prior studies have shown that theory-driven simulation offers a robust foundation for early validation of intelligent systems, especially when access to real patient data is constrained [43], [28], [31]. In this sense, the simulation not only provides a sound testing ground but also strengthens the overall design process, bridging the gap between theoretical modeling and practical deployment.

Descriptive analysis of satisfaction scores:
This section explores how the fuzzy inference system translates multidimensional patient input into overall satisfaction scores. A total of 100 synthetic patient profiles were evaluated using the fuzzy model, with each profile reflecting plausible combinations of key healthcare experience indicators.

The resulting satisfaction scores range from 2.74 to 8.38, with a mean of 6.33 and a standard deviation of 1.15. The median score stands at 6.52, suggesting a slight tendency toward higher satisfaction levels. While extreme values are rare, the model captures a meaningful variety of satisfaction levels across the dataset.

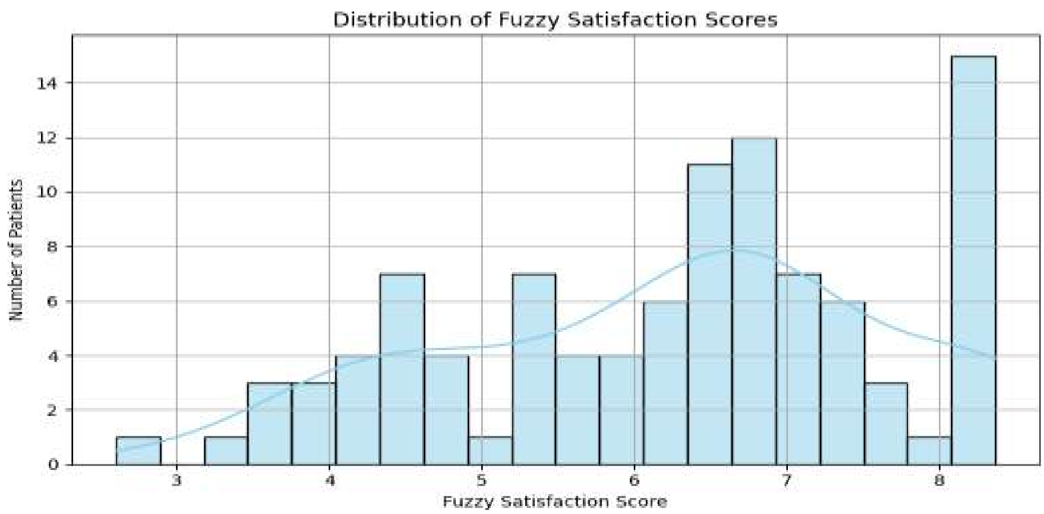

Figure 2:- Distribution of Fuzzy Satisfaction Scores

As shown in Figure 2, most scores are concentrated between 5.5 and 7.5. This indicates that the system tends to produce moderate to moderately high satisfaction levels. A few cases fall below 4, reflecting clearly negative experiences. On the upper end, while the model does produce scores above 8.0, none of the patients received a score beyond 8.5. This plateau suggests a potential saturation effect in the inference process.

Such behavior may result from the structure of the output membership functions or from the absence of highly reinforcing rules that would drive scores toward the upper extreme. Nevertheless, this pattern aligns with observations in real healthcare settings, where extremely high or extremely low satisfaction ratings are uncommon. In summary, the fuzzy system yields continuous and interpretable satisfaction scores that capture the diversity of patient experiences without producing unrealistic extremes. The consistency and balance observed in the results support the model's applicability in simulated healthcare evaluations and lay the groundwork for future real-world deployment.

Influence of key satisfaction criteria:
To explore how each input dimension contributes to the final satisfaction score, a correlation analysis was performed between the eight criteria and the fuzzy output. This step helps assess whether the system behaves in a way that reflects intuitive and clinically relevant priorities in patient experience.

As presented in Figure 3, three variables emerge as the most influential. Patient Involvement shows the strongest correlation with the overall score (r = 0.68), followed closely by Communication and Information (r = 0.64), and Reception and Accessibility (r = 0.57). These results suggest that patients who feel actively involved in their care, well-informed, and properly received are more likely to be rated highly by the fuzzy system.

This internal pattern reflects the logic embedded in the rule base. Many rules are designed to reward strong engagement and clear communication, especially when coupled with favorable perceptions of care outcomes. These variables often act as amplifiers of satisfaction, contributing more weight than purely structural elements like infrastructure or billing.

Although dimensions such as Cost and Billing Perception or Environment and Infrastructure show weaker correlations, they still play a role in shaping the final score. Their more modest influence may be explained by the distribution of simulated values or by the relatively neutral weight they hold within the current set of inference rules. Overall, the fuzzy model appears to emphasize key relational aspects of care when determining satisfaction. This alignment between input behavior and output scoring supports the internal consistency of the system. It also reinforces the interpretability of the model, a key strength when compared to more opaque computational approaches.

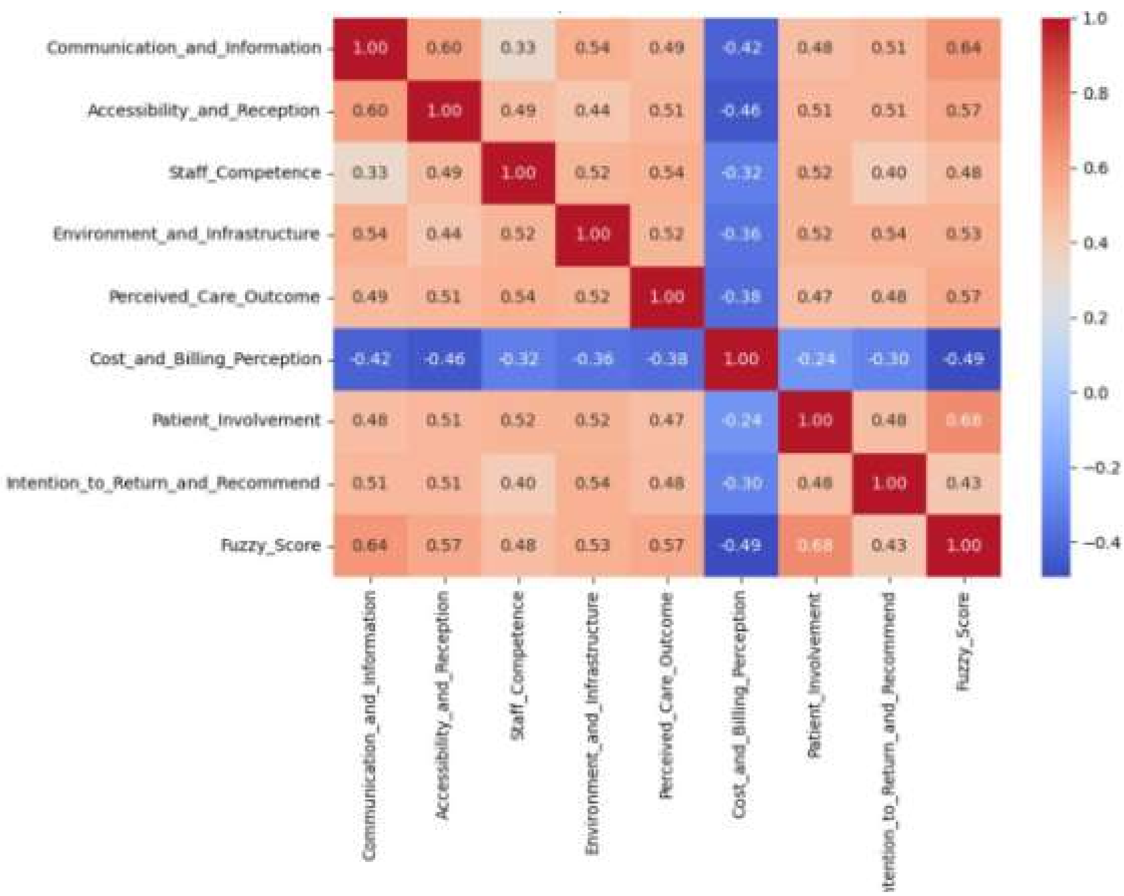

Figure 3:- Correlation matrix of satisfaction criteria and fuzzy score

In addition to the correlation analysis, three-dimensional surface plots were introduced to provide a more intuitive view of how pairs of satisfaction criteria interact within the fuzzy system. These visualizations offer a window into the internal reasoning process of the model, highlighting how certain combinations of inputs contribute to the final satisfaction score.

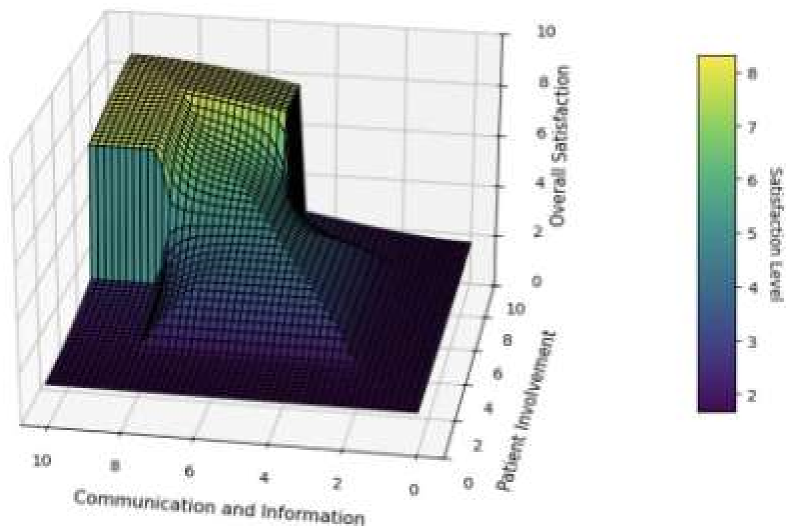

Figure 4:- Surface plot of patient satisfaction in relation to Communication and Information and Patient Involvement

Figure 4 shows how satisfaction varies according to the level of communication and information provided, combined with the degree of patient involvement in care decisions. The plot reveals that satisfaction increases substantially when both dimensions are rated highly. However, if either communication or involvement is perceived as weak, satisfaction remains low or stagnant. This highlights the importance of active dialogue and patient-centered practices in fostering positive care experiences.

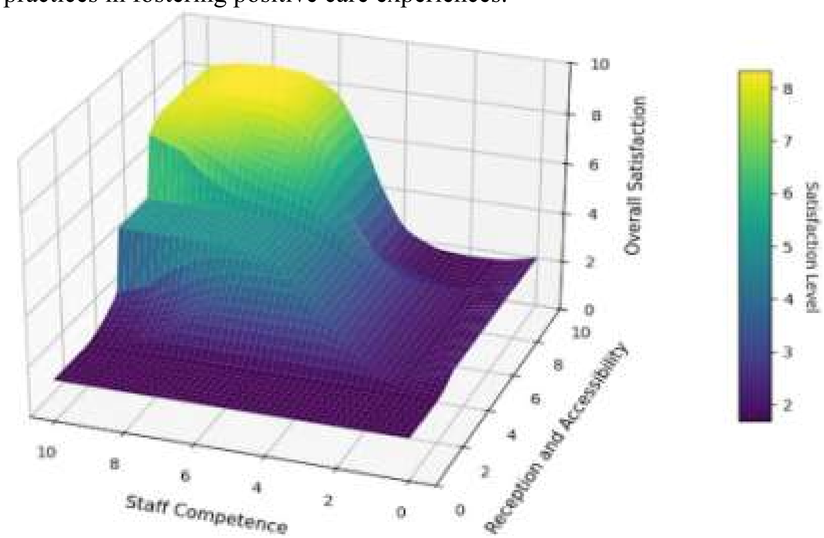

Figure 5:- Surface plot of patient satisfaction as influenced by staff competence and reception and accessibility

In Figure 5, the surface depicts the impact of staff competence and the quality of reception and accessibility on patient satisfaction. The results show a steep rise in satisfaction when both factors are rated positively. Notably, poor staff competence leads to a sharp drop in satisfaction, even when reception is adequate. This suggests that patients place strong emphasis on the professionalism and empathy of healthcare providers, perhaps even more than on logistical aspects.

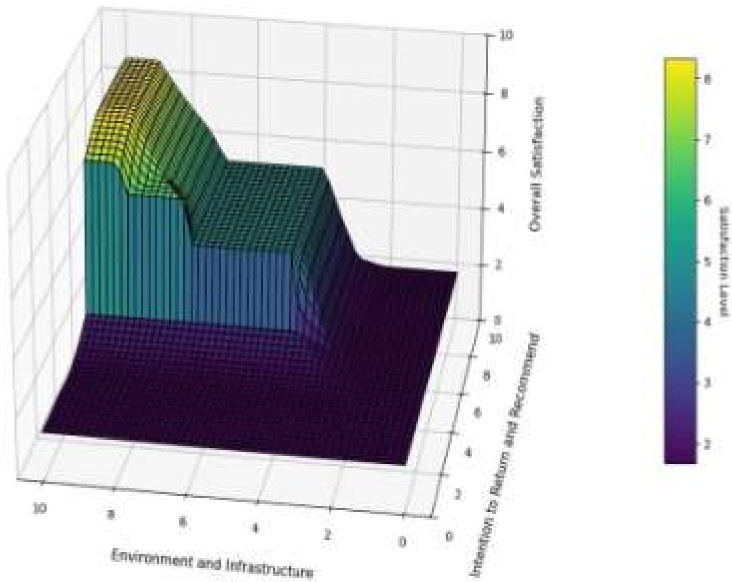

Figure 6. Surface plot of patient satisfaction according to Environment and Infrastructure and Intention to Return and Recommend

Figure 6 explores how the environment and infrastructure of care, combined with the patient's intention to return or recommend the facility, contributes to overall satisfaction. The plot reveals a more gradual increase across the surface, with higher satisfaction observed only when both the environment and loyalty indicators are favorable. This suggests that trust and comfort, while not always immediately impactful, reinforce each other and contribute to lasting satisfaction over time.

Illustrative Patient Profiles:
To assess the interpretability and internal consistency of the fuzzy satisfaction model, three representative patient profiles were selected. These cases correspond to low, medium, and high satisfaction levels and are presented in Table 3. Each profile illustrates how the system combines patient-reported inputs into a single satisfaction score that remains both transparent and clinically meaningful.

Table 3. Representative patient profiles with low, medium and high satisfaction scores

Variable	Low	Medium	High
Communication	2.4	5.6	9.4
Accessibility	2.2	7.3	9.1
Competence	3.9	3.4	9.1
Infrastructure	4.8	5.4	9.2
Outcome	5.0	4.6	9.9
Billing	7.7	4.1	1.3
Involvement	4.1	7.2	9.7
Recommendation	7.8	3.2	9.2
Fuzzy Score	2.60	6.44	8.37

The low-satisfaction profile reflects a patient who reported limited communication, poor accessibility, and a low level of involvement in their care. Although this patient expressed moderate satisfaction with infrastructure and care outcomes, the relational experience was clearly lacking. As a result, the final score was significantly reduced, illustrating how the fuzzy system gives strong weight to interpersonal dimensions.

The medium-satisfaction profile presents a more balanced case. The patient reported excellent accessibility and felt actively involved in the care process. However, scores for staff competence and treatment outcome were moderate, and the willingness to recommend the service was low. This combination of contrasting elements led the model to produce an intermediate satisfaction score, showing that it is capable of integrating diverse perceptions into a coherent and reasonable output.

The high-satisfaction profile corresponds to several patients who received the same maximum score of 8.37. Although their values varied slightly, all of them reported very high ratings across the most influential dimensions, including communication, staff competence, perceived care outcomes, and loyalty. In this case, a range of values is presented for each variable to reflect this shared pattern. Interestingly, some of these patients gave relatively low scores for billing transparency. Nevertheless, the overall satisfaction remained high, confirming that the model prioritizes essential aspects of the care experience when synthesizing the final score.

Together, these three profiles illustrate how the fuzzy system captures the subtle interplay between clinical, relational, and environmental factors. It provides scores that are not only internally consistent but also aligned with intuitive interpretations of patient satisfaction. This interpretability strengthens the model’s credibility and suggests that it may offer valuable insights in future real-world applications.

Discussion:-

Improving the quality of healthcare services remains a global priority, particularly as systems strive to align clinical excellence with patient-centered care. In this context, patient satisfaction has emerged as a key performance indicator, directly influencing health outcomes, service utilization and policy decisions [1, 2, 3]. Beyond its evaluative function, satisfaction reflects the patient’s subjective perception of the care experience, encompassing relational, organizational and environmental dimensions [4, 5, 6]

This study set out to explore whether a fuzzy logic-based approach could meaningfully assess patient satisfaction across multiple care dimensions. By simulating 100 diverse patient profiles, we were able to observe how the system behaves, test the consistency of its internal rules, and evaluate how linguistic inputs lead to structured, interpretable satisfaction scores.

Interpretation of results:

The distribution of satisfaction scores was well-balanced, with most patients falling in the medium to high satisfaction range. Certain criteria, particularly staff competence and physical environment, were consistently rated highly. This suggests that these aspects are often perceived as institutional strengths. In contrast, dimensions like communication and billing showed more variability, which reflects common challenges in provider-patient interactions and financial transparency in healthcare [5, 10].

The fuzzy system itself responded logically to variations in input. Profiles with favorable ratings across key areas such as communication, treatment outcomes, and patient engagement generally produced high satisfaction scores, often exceeding 85 percent. Meanwhile, cases with poor accessibility or disappointing care experiences resulted in lower scores. These findings confirm that the inference rules operate effectively, yielding coherent and interpretable results [13][45].

Relevance to Existing Literature:

Our findings are in line with existing research that supports the use of fuzzy logic in healthcare evaluation. Unlike rigid quantitative tools, fuzzy systems are well-suited to interpret the subjective and often nuanced nature of patient feedback while maintaining consistency in reasoning [31, 24]. In this context, using simulated data should not be viewed as a limitation but as a strategic step in the validation process. Several studies have highlighted the importance of theory-driven simulation as a prerequisite to full-scale empirical testing [5, 46]. The consistency observed across varied simulated cases reinforces the system's robustness and suggests its potential relevance in real-world healthcare applications.

Practical Implications:

The structure of the system allows for integration into diverse clinical workflows. Healthcare institutions could use it to generate satisfaction dashboards, helping managers monitor trends and respond proactively to early signs of dissatisfaction. This application aligns with current calls for intelligent, human-centered decision-support solutions in healthcare [16, 33]. In addition, by including dimensions such as patient involvement and willingness to recommend [47], the model extends beyond simple satisfaction measurement. It begins to capture more complex elements like trust, loyalty, and patient engagement, which are becoming increasingly central in value-based care delivery [48] [21, 49].

Limitations and Future Work:

Although the simulation confirms that the model operates consistently and produces coherent outputs under controlled conditions, further testing with real patient data remains essential to evaluate its capacity to generalize beyond the simulation. This reflects the distinction between internal consistency, which measures the reliability of the model's logic and structure, and external validity, which assesses how well it performs in real-world scenarios [24, 50]. Despite the limited scope of the synthetic dataset, the results demonstrate that fuzzy logic offers a unique balance of clarity, flexibility, and interpretability. These qualities are especially relevant in patient satisfaction assessment, where perceptions are inherently subjective and often nuanced [8, 51].

The system's transparent reasoning and ability to handle imprecise inputs position it as a valuable tool for decision support in healthcare environments.

Conclusion:-

Improving the quality of healthcare services remains a global priority, particularly as systems strive to align clinical excellence with patient-centered care. In this context, patient satisfaction has emerged as a key performance indicator, directly influencing health outcomes, service utilization and policy decisions [1, 2, 3]. Beyond its evaluative function, satisfaction reflects the patient's subjective perception of the care experience, encompassing relational, organizational and environmental dimensions [4, 5, 6]

This study introduced and simulated a fuzzy logic-based system for evaluating patient satisfaction, grounded in eight carefully selected dimensions relevant to healthcare experiences. By translating subjective perceptions into structured numerical scores, the model provides a more interpretable and holistic view of satisfaction, while preserving the richness of patient feedback.

The simulation of 100 patient profiles made it possible to explore the behavior of the system across a wide range of scenarios. The results show that the fuzzy model responds in a coherent way to variations in input variables. It assigns higher satisfaction when communication, care quality, and infrastructure are rated positively, and lower satisfaction when issues are reported in access, cost, or personalized attention. This consistency confirms the relevance of the rules and membership functions implemented in the system.

Beyond theoretical validation, the work points to concrete practical applications. The fuzzy satisfaction engine can be integrated into hospital dashboards or interactive decision-support tools to help healthcare professionals monitor trends, detect weaknesses, and respond more quickly to patient concerns. Because it is both interpretable and adaptable, the model can be deployed in a variety of healthcare environments, including in settings with limited resources.

Future work will consist in applying the system to real data collected through patient surveys. This empirical validation will make it possible to evaluate the accuracy, sensitivity, and robustness of the model. Further developments may include enriching the rule base with machine learning techniques or embedding the fuzzy engine within a broader multi-agent architecture.

In summary, this research shows that fuzzy logic provides a powerful and intuitive method for capturing the complexity of patient satisfaction. It offers a balance between precision and flexibility and opens promising perspectives for patient-centered evaluation in healthcare.

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