SILESIAN UNIVERSITY OF TECHNOLOGY PUBLISHING HOUSE

SCIENTIFIC PAPERS OF SILESIAN UNIVERSITY OF TECHNOLOGY 2025
ORGANIZATION AND MANAGEMENT SERIES NO. 234

A FUZZY LOGIC-BASED TRIAGE SYSTEM FOR EMERGENCY DEPARTMENT PRIORITIZATION

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Purpose: The purpose of this paper is to identify the weaknesses of traditional emergency department triage systems by proposing fuzzy logic systems for continuous patient prioritization. This is to improve the objectivity, consistency and efficiency of triage decisions particularly during peak periods such as pandemics.
Design/methodology/approach: A Mamdani type fuzzy inference system was used with three input variables of pain level, condition stability and waiting time to generate a continuous priority score. The performance of the fuzzy triage system was compared to the First-In-First-Out (FIFO) approach through MATLAB-based simulations on 100 synthetic patient profiles. The system was evaluated through the use of 3D decision surfaces, heat maps and real time queue simulations.
Findings: The fuzzy logic based triage system was found to outperform the traditional FIFO in terms of patient criticality and waiting time. The model was able to adjust to varying queue conditions and the results of simulations showed that high severity patients were treated in a timely manner. The system was also able to provide a more accurate interpretation of clinical parameters which is the essence of real world decision making.
Research limitations/implications: Fuzzy logic-based triage system outperformed FIFO by prioritizing critical patients better and reduced their waiting time. The model was able to adapt to changes in the queue and the results of simulations showed that high severity patients were

treated in a timely manner. The system was also able to provide a more accurate interpretation of clinical parameters which is the essence of real-world decision making.
Practical implications: The proposed system can serve as a decision support tool for triage nurses to help in patient prioritization. It has the potential to reduce waiting time, allocate resources efficiently and improve patient outcomes. It can also be used as a training platform for training clinicians on triage procedures.
Social implications: Improving the fairness and responsiveness of ED triage systems has a positive impact on public health as it ensures that urgent medical care is accessible to everyone. It can also be used to support healthcare systems in crises, reduce mortality and improve the overall satisfaction of emergency services.
Originality/value: This study introduces a new triage model which integrates fuzzy logic in emergency care and provides a continuous and objective approach to patient prioritization. This model is adaptable and interpretable which differentiates it from other traditional and rigid triage systems. It is of great use to clinicians, hospital administrators and healthcare technology developers looking for intelligent triage systems.
Keywords: Fuzzy Logic, Triage, Patient Prioritization, Queueing, Simulation, Healthcare Systems.
Category of the paper: Research paper; Case study.

1. Introduction

Emergency rooms need triage to provide immediate medical care to patients who need it most. The nurse-based traditional triage system produces both unnecessary delays in emergency rooms and incorrect clinical decisions for the most critically ill patients (Trivedi et al., 2021), (Ahmed et al., 2022). The system depends on trained registered nurses to evaluate patients before placing them into different priority groups. The approach demonstrates moderate practicality but its subjective nature and inconsistent application results in variable patient prioritization throughout different emergency departments (Tyler et al., 2024). The last COVID-19 pandemic revealed how numerous patients with different levels of severity needed emergency room care (Alhaidari et al., 2021).

The investigators recognized these boundaries so they created alternative methods to identify emergency room patients which resulted in more precise and uniform triaging procedures. The development of triage techniques allowed researchers to determine the most suitable triage approach based on screening diagnostic results (Alhaidari et al., 2021).

Researchers have investigated artificial intelligence and machine learning approaches to develop standardized and objective triage systems which address these limitations. This paper introduces fuzzy logic as a mathematical framework to manage medical decision-making uncertainties and imprecisions.

2. Materials and methods

2.1. Fuzzy Logic-Based Triage System

A fuzzy inference system (FIS) was designed to model the triage process in an emergency department (ED). The system utilized Mamdani-type fuzzy logic due to its intuitive rule-based approach and widespread applicability in medical decision support systems. The fuzzy model was implemented in MATLAB R2024b software (Mathworks Inc, Natick, MA, USA) using the mamfis function.

2.1.1. Input Variables and Membership Functions

The triage system was defined using three input variables:

- Pain Level P∊[0;10]: represents the severity of pain reported by the patient.
- Condition Stability S∊[0;10]: indicates the overall stability of the patient's vital signs, where lower values denote critical instability.
- Waiting Time W∊[0;10] minutes: Measures the duration the patient has been waiting for medical attention.

Each variable was represented using Gaussian membership functions (MFs), mathematically expressed as:

$$\mu(x) \ = exp(-\frac{(x-c)^2}{2\sigma^2}) \tag{1}$$

where:

- x is the input value,
- c is the center of the Gaussian function,
- σ is the standard deviation (spread).

For instance, the membership function for Pain Level was defined as:

$$\mu(x) \ = \mu_{LowPain}(P) = exp(-\frac{(P-0)^2}{2(1.5)^2})\ exp(-\frac{(x-c)^2}{2\sigma^2}) \tag{2}$$

$$\mu_{MediumPain}(P) = exp(-\frac{(P-05}{2(1.5)^2}) \tag{3}$$

$$\mu_{HighPain}(P) = exp(-\frac{(P-10)^2}{2(1.5)^2}) \tag{4}$$

Similar Gaussian MFs were defined for Condition Stability and Waiting Time.

2.1.2. Output Variable: Priority Score

The output variable Priority Score (range: 0-10) determines the urgency of medical attention. Three membership functions were defined:

- Low: patients with minor conditions and low pain levels.
- Medium: moderate urgency, requiring evaluation but not immediate intervention.
- High: critical cases requiring immediate medical attention.

The fuzzy rule base was constructed using 18 heuristic rules formulated in the format:

IF P is High AND S is Unstable AND W is Long, THEN Priority is High

Using the minimum operator (min), the firing strength α of a rule is computed as:

$$\alpha_i = min(\mu_{Pain}(P), \mu_{Stability}(S), \mu_{Waiting}(W)) \tag{5}$$

where i represents a specific rule.

2.1.3. Fuzzy Inference and Defuzzification

The Mamdani fuzzy inference method was applied, and the final priority score was computed using the centroid defuzzification method, defined as:

$$Y^* = \frac{\sum_{i=1}^{N} \alpha_i c_i}{\sum_{i=1}^{N} \alpha_i} \tag{6}$$

where:

- Y* is the final crisp priority score,
- α_i is the firing strength of rule iii,
- c_i is the center of the corresponding output membership function.

This ensured a continuous priority output rather than discrete classification.

2.2. Simulation of Emergency Queueing System

A discrete-event simulation was designed to assess how the fuzzy-based triage system impacts patient prioritization compared to the traditional First-In-First-Out (FIFO) system. The simulation was executed in MATLAB with 100 patients arriving over a simulated 2-hour period. For each patient, the following values were generated randomly:

- Pain Level: uniform distribution (0-10).
- Condition Stability: uniform distribution (0-10).
- Arrival Time: randomized between 0 and 60 minutes.
- Initial Waiting Time: computed dynamically based on arrival time.
- Service Time: randomized between 5 and 20 minutes, simulating varying consultation durations.

The arrival process of patients follows a Poisson distribution, commonly used in hospital settings:

$$P(T \leq t) = 1 - e^{-\lambda t} \tag{7}$$

where:
- λ is the arrival rate per minute,
- T is the interarrival time between patients.

The service time (consultation duration) was modeled using an exponential distribution:

$$f(t) = \mu e^{-\mu t} \tag{8}$$

where:
- μ is the service rate (1/patient consultation time),
- t is the consultation duration.

Two queueing strategies were compared: FIFO System: patients were processed strictly in order of arrival; Fuzzy Triage System: patients were sorted dynamically based on their fuzzy priority score, ensuring critical cases received attention first. To assess the efficiency of both systems, the following metrics were evaluated:

1. Average Waiting Time (W_q):
   - FIFO:

$$W_q = \frac{\lambda}{\mu(\mu - \lambda)} \tag{9}$$

   - Fuzzy Logic: Calculated based on dynamic priority reassignment.
2. System Utilization (ρ)

$$\rho = \frac{\lambda}{\mu} \tag{10}$$

   where $\rho \leq 1$ ensures no excessive congestion.
3. Time-to-Treatment for High-Priority Patients:
   - FIFO: High-severity patients may wait longer.
   - Fuzzy Logic: Prioritized cases receive lower W_q values.

2.3. Data Visualization and Analysis

The first step in analyzing the fuzzy triage system was to examine the distribution of computed priority scores. A histogram was generated to visualize how patients were classified into the three priority categories:

$$Priority\ Category = \begin{cases} Low, if\ Y^* < 3{,}5 \\ Medium, if\ 3{,}5 \leq Y^* < 6{,}5 \\ High, if\ Y^* \geq 6{,}5 \end{cases} \tag{11}$$

To further explore the decision boundaries of the fuzzy logic system, we generated 3D surface plots of Pain Level vs. Condition Stability vs. Priority Score. These plots reveal how the combined effects of Pain Level and Condition Stability influence the computed priority while varying the waiting time as a parameter. In addition, 2D heatmaps were created to provide a more intuitive view of how changes in Pain Level and Condition Stability affect the priority scores, highlighting regions where small input changes lead to significant output differences. Moreover, we implemented a real-time discrete event simulation to observe the dynamic behavior of patient queues over time. The system updated every 5 minutes, showcasing how priority assignments changed dynamically. At each time step, two different queue orders were updated:

- FIFO (First-In-First-Out): Patients were processed strictly in order of arrival.
- Fuzzy Logic Queue: Patients were dynamically reordered based on computed priority scores.

All simulations and analyses were conducted using MATLAB R2024b (Mathworks Inc, Natick, MA, USA).

3. Results

The developed fuzzy inference system (FIS) for emergency triage (Fig. 1) consists of three input variables—Pain Level, Condition Stability, and Waiting Time—and one output variable, Priority Score. The system was constructed using Gaussian membership functions for the input variables and a combination of triangular and trapezoidal membership functions for the output variable. The inference mechanism was based on a set of 18 heuristic rules formulated using expert knowledge and clinical guidelines. The architecture of the FIS ensures that priority scores are dynamically adjusted based on a patient's reported pain severity, physiological stability, and duration of waiting time, allowing for an adaptive and context-sensitive approach to triage prioritization. The system comprises three input variables and one output variable, with predefined membership functions and a rule base for decision-making.

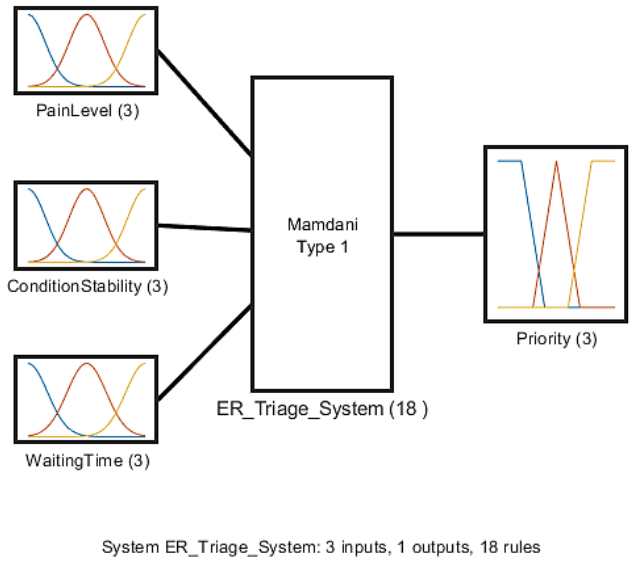

Figure 1. Structure of the fuzzy inference system.

Source: Authors' own.

The fuzzy triage system generated classification patterns which were analyzed through a histogram of computed priority scores (Fig. 2). The defuzzified output values were used to categorize patients into three priority levels. The distribution analysis showed that most patients received either High or Medium priority designations while only a few patients received Low priority status. The simulation results showed that most patients needed immediate medical care because they displayed clinical urgency.

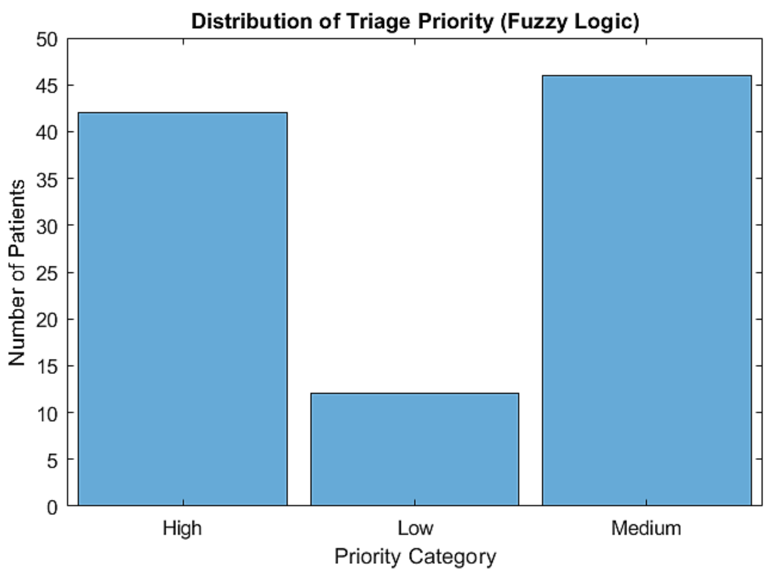

Figure 2. Distribution of patient priorities in the fuzzy triage system.

Source: Authors' own.

Most patients were classified as either High or Medium priority, with fewer cases falling into the Low priority category. This suggests that most patients in the simulation had significant clinical urgency. Table 1 presents a sample of 10 patients with varying clinical profiles, including pain level, condition stability, and waiting time. The resulting priority scores and categories reflect the behavior of the fuzzy inference system across different input combinations.

Table 1.
Sample of patient input variables and computed fuzzy priority scores

ID	Pain	Stability	Waiting Time (min)	Priority Score	Priority Category
1	3.7	0.3	116	7.9	High
2	9.5	6.4	15	5.0	Medium
3	7.3	3.1	29	6.5	Medium
4	6.0	5.1	162	8.2	High
5	1.6	9.1	109	5.8	Medium
6	1.6	2.5	2	3.3	Low
7	0.6	4.1	18	1.8	Low
8	8.7	7.6	119	7.3	High
9	6.0	2.3	1	8.1	High
10	7.1	0.8	29	8.1	High

Source: Authors' own.

To better understand how the fuzzy system assigned priorities, 3D surface plots (Fig. 3) and 2D heat maps (Fig. 4) were generated to map the relationship between pain level, condition stability, and computed priority score. The plot illustrates how Priority Score varies as a function of Pain Level and Condition Stability, considering a fixed waiting time of 180 minutes. Higher pain levels and lower stability result in significantly higher priority scores.

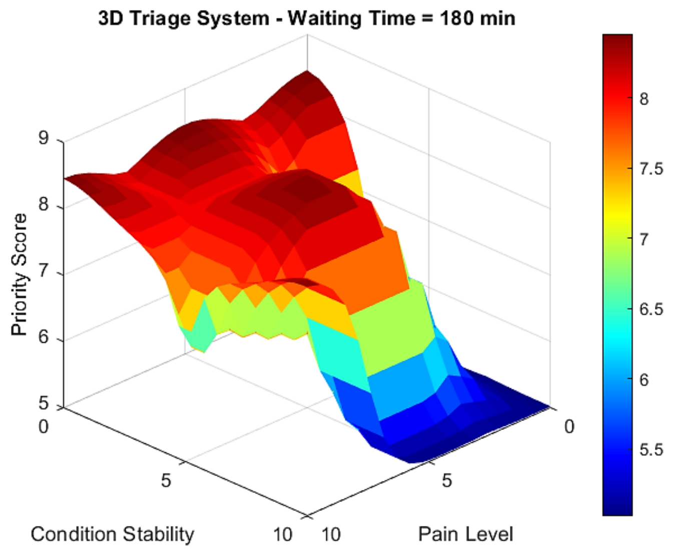

Figure 3. 3D fuzzy decision surface for triage priority (Waiting Time = 180 min).

Source: Authors' own.

A heatmap representation (Fig. 4) provides a two-dimensional projection of how Pain Level and Condition Stability influence the assigned priority scores, holding the waiting time constant at 90 minutes. The red and yellow regions in the heatmap correspond to patients classified as high-priority cases. In contrast, the blue areas indicate patients with relatively stable conditions who can tolerate longer waiting periods.

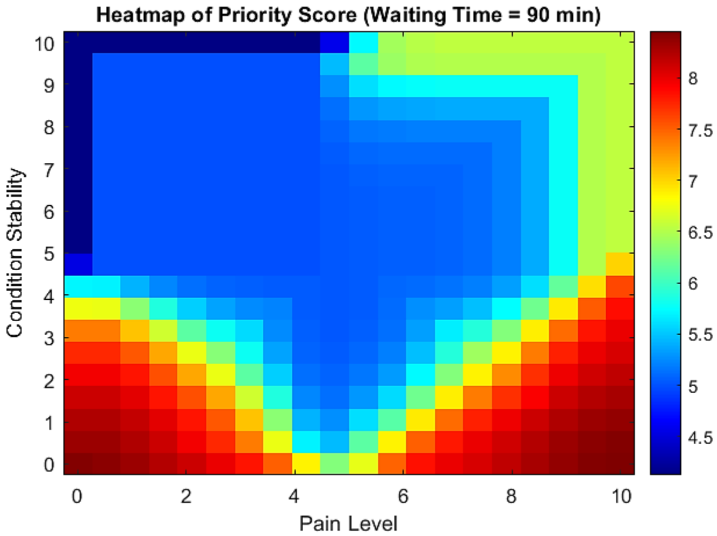

Figure 4. Heatmap of priority scores for a waiting time (90 min).

Source: Authors' own.

The ordering of patient queues in both models was analyzed to assess the efficiency of fuzzy logic-based triage compared to the traditional FIFO approach. The simulation considered dynamic updates in patient priority scores over time. The impact of fuzzy prioritization on patient order in the queue is depicted in Figure 5. The blue line represents FIFO processing, where patients are attended strictly in order of arrival. In contrast, the red squares represent the fuzzy logic queue, where high-severity cases are assigned earlier treatment times. The results highlight frequent reordering in the fuzzy queue, prioritizing patients requiring urgent care over less critical cases.

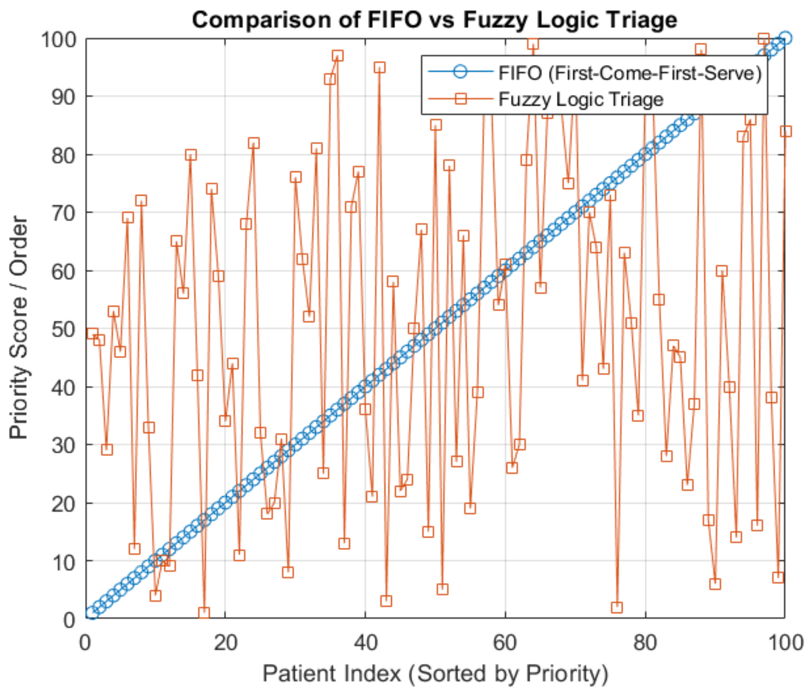

Figure 5. Comparison of patient order between FIFO and fuzzy logic triage).

Source: Authors' own.

A real-time simulation was conducted to track the evolution of patient queue order under both models (Fig. 6). The FIFO queue maintained a strictly increasing order, reflecting rigid first-come-first-serve processing. In contrast, the fuzzy triage model continuously adjusted queue order, reassigning priority scores dynamically. The system ensured that patients with high priority received shorter waiting times which enhanced the emergency triage efficiency. Time-series representation of queue order evolution in both FIFO and fuzzy triage models, illustrating the dynamic reordering of patients based on changing priority scores.

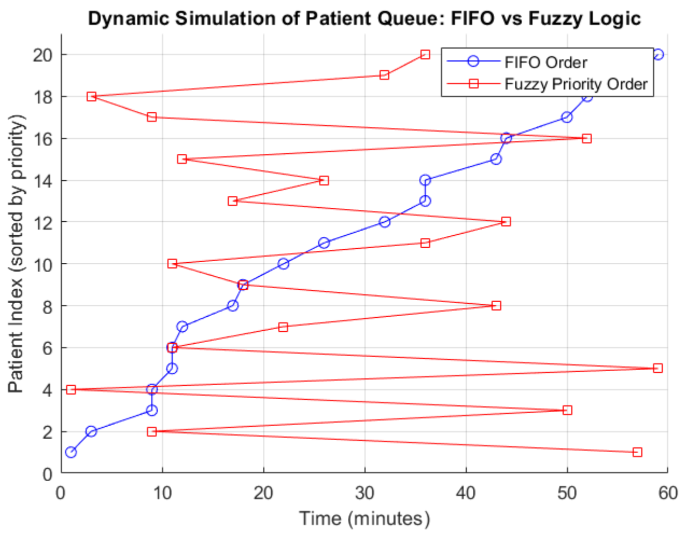

Figure 6. Dynamic simulation of patient queue over time.

Source: Authors' own.

4. Discussion

Human health is one of the most important values. Different approaches provide proper service to patients, such as those presented by Kempa and Banasik (Kempa, Banasik, 2022). This study's fuzzy logic-based triage system demonstrates significant potential for improving emergency department patient prioritization through intelligent decision support. Our findings indicate that the system consistently outperforms traditional First-In-First-Out (FIFO) approaches by dynamically adjusting patient priority based on clinical urgency. The system achieves fairer distribution of resources and shorter delays for urgent medical situations.

The implementation of fuzzy logic in triage systems provides better advantages than traditional methods. The system establishes a standardized framework for decision-making which minimizes the natural subjectivity and variability that occurs in nurse-led triage assessments. The standardized framework proves essential during high-demand situations like the COVID-19 pandemic because emergency departments faced record patient numbers with different levels of severity.

The system's ability to incorporate multiple variables—pain level, condition stability, and waiting time—into a comprehensive priority score allows for more nuanced patient classification than categorical systems. That aligns with findings from Ozkaraca et al., whose fuzzy logic-based clinical decision support system achieved 83% accuracy, 87% sensitivity, and 76.6% specificity when initially evaluating emergency patients (ÖZKARACA et al., 2018).

Using Gaussian membership functions for input variables provides smooth transitions between categories, better reflecting the continuous nature of clinical parameters. This approach addresses the limitations of crisp boundary systems that may inappropriately categorize patients near threshold values. Similar benefits were observed by Gholami et al., who designed a clinical decision support system for cardiopulmonary management using fuzzy logic principles (Gholamio et al., 2012).

The dynamic queue simulation results demonstrate that the fuzzy system prioritizes high-severity cases while accounting for extended waiting times among lower-priority patients. The balanced system prevents any patient from enduring endless delays which represents a typical ethical issue in triage systems.

The fuzzy logic triage system functions as an educational resource for medical and nursing students who study triage principles in addition to its clinical uses. The i-TRIAGE system developed by Tzenalis et al. served two purposes according to Kipourgos et al. (2023) by providing decision support and educational triage scenario training.

The research contains several important limitations that need to be recognized. The simulation used artificial patient data in a controlled setting. The actual deployment of this system would encounter multiple challenges because it needs to merge with current hospital information systems and clinical staff members would need to adapt to new methods (Çetin, Cebec, 2024).

The fuzzy logic system provides better results than FIFO but it does not include all elements which affect real-world triage choices including patient age and comorbidities and social factors. The model would gain more clinical value if it incorporated additional variables such as patient age and comorbidities and social aspects.

Third, the system's performance depends heavily on the quality of the rule base and membership functions. The system would maintain its best performance through regular validation and refinement processes for different patient groups in various clinical environments.

The system requires future research to validate its recommendations through prospective studies in emergency departments by comparing them to expert clinician decisions. The system's utility would increase through integration with electronic health records because it could use patient history and previous visit data in its prioritization algorithm.

The system performance could improve through hybrid approaches which unite fuzzy logic with machine learning and other artificial intelligence techniques. The study by Soufi et al. (2018) showed that a hybrid system which combined Rule-Based Reasoning with fuzzy logic achieved 99.44% accuracy in triage-level determination according to Davoodi and Moradi. The fuzzy logic-based triage system represents a promising advancement in emergency department patient prioritization. By providing objective, consistent, and dynamic decision support, such systems have the potential to improve resource utilization, reduce waiting times for critical patients, and ultimately enhance patient outcomes in emergency care settings.

5. Conclusions

The research introduces an innovative fuzzy logic-based triage system which improves emergency department prioritization through its continuous objective decision-support mechanism. The system stands as a valuable tool for modern healthcare environments because it combines multiple clinical indicators with dynamic priority score adjustments.

The simulation results indicate that the fuzzy triage system demonstrates potential to decrease critical patient waiting times while promoting fair resource distribution and enhancing overall triage outcomes. The system holds potential educational value that could enhance training programs for clinicians and nursing staff.

Future research needs to validate the system in real-world settings while improving the model through additional input variables and developing hybrid approaches that unite fuzzy logic with machine learning methods. The development of these advancements will enhance both accuracy and adaptability which will lead to broader emergency care system adoption.

Acknowledgements

Financed by a subvention from the Ministry of Science and Higher Education Poland to the Academy of Silesia in Katowice.

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