Informing Science: the International Journal of an Emerging Transdiscipline

An Official Publication of the Informing Science Institute InformingScience.org

Inform.nu

Volume 28, 2025

OPTIMIZING HEALTHCARE SERVICE DELIVERY USING IMPROVISED FUZZY LOGIC ALGORITHM

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ABSTRACT

Aim/Purpose	To develop a Deep Fuzzy Logic (DFL) model linking all hospital departments – inpatient, outpatient, and A&E. To maximize staff distribution and bed capacity using linear optimization techniques.

Accepting Editor Eli Cohen │ Received: October 19, 2024 │ Revised: November 30, 2024 │ Accepted: December 14, 2024.

Cite as: Sarasu, R., Kumar, S., Thomas, M., Bhimavarapu, J. P., Shyamala, L., Gupta, R. (2025). Optimizing healthcare service delivery using improvised fuzzy logic algorithm. *Informing Science: The International Journal of an Emerging Transdiscipline, 28,* https://doi.org/10.28945/5411

Background	Growing pressure on healthcare systems calls for efficient use of resources when extra money is not accessible. Rising demand and limited capacity in every field of medicine need comprehensive modeling for hospitals.
Methodology	We developed a DFL model combining outpatient, hospital, and A&E services. This model estimates demand for all specialties, considers patient pathway uncertainty, and projects required bed capacity and staff demands by linear optimization using discrete event simulation.
Contribution	Complete hospital models are rare; recent studies demonstrate the rising use of numerous operational research (OR) techniques. Deep Fuzzy Logic (DFL) models are becoming more and more interesting when combined with optimization, simulation, and forecasting.
Findings	The model provides a means of short-term and long-term strategic planning decision support to crucial decision-makers. Our DFL model showed a 15% gain in bed utilization efficiency and a 10% drop in staff shortages compared to more traditional methods.
Recommendations for Researchers	Investigations should prioritize the validation of the algorithm in various healthcare environments to assess its efficacy in clinical application.
Future Research	In future research, this work can be enhanced using several deep learning algorithms to achieve better accuracy and performance.

Keywords	deep fuzzy logic, healthcare modeling, discrete event simulation, linear optimization, hospital resource management

INTRODUCTION

BACKGROUND

In recent years, the demand and capacity limits in the healthcare system have achieved a faster growth rate and necessity (Beaulieu & Bentahar, 2021). The financial issue and charges of utilization of the resources have faced more drastic changes and increasing factors in the last couple of years (Abdalkareem et al., 2021). Hospitals especially have an increasing demand for all sorts of treatments and services; thus, it is necessary to maximize resource usage to retain the quality of treatment.

CHALLENGES

The main challenge of this research is focusing on more waiting time for the patients, applicable in both house and outpatient scenarios. Also, there is a shortage of hospital staff, and a large amount of scarcity arises from the occupancy of beds (Usak et al., 2020). Conventional resource management methods often overlook the interrelated character of healthcare services, causing inefficiencies and less-than-perfect outcomes (Halawa et al., 2020).

PROBLEM DEFINITION

Not often is a whole hospital model encompassing all services and specialties applied (Saravanan et al., 2023). Most modern models view hospital departments independently, thereby neglecting the interconnectedness influencing general performance (Fatani et al., 2024). To close this discrepancy, a complete model capable of forecasting demand, replicating patient pathways, and optimal resource allocation over the entire hospital is required (Choudhry et al., 2024).

Objectives

The main objectives of this study are:

1. To develop a Deep Fuzzy Logic (DFL) model linking all hospital departments – including inpatient, outpatient, and A&E ones.
2. To project demand for every specialization using state-of-the-art statistical tools.
3. To repeat patient pathways over uncertain discrete event simulation.
4. To maximize staff distribution and bed capacity by means of linear optimization techniques.

Novelty and Contributions:

The proposed DFL model blends forecasting, modeling, and optimization into a single framework. This hybrid technique provides a full picture of hospital operations, therefore allowing more precise and efficient utilization of resources. Among the noteworthy contributions are:

- Combining forecasting, modeling, and optimization techniques specifically for hospital environments.
- An integrated model that is able to capture the connections and complexity among healthcare services.
- A tool for decision assistance improving operational performance and guiding strategic planning.

Related Works

Techniques such as deep learning, reinforcement learning, and hybrid predictive models have significantly improved patient demand forecasting and resource optimization. Highlighting how these approaches address challenges like interdepartmental integration and system-wide modeling would contextualize the DFL model's contribution. Positioning DFL alongside these methods emphasizes its unique advantage in offering a holistic, integrated framework that combines forecasting, modeling, and optimization, thereby addressing gaps in existing methodologies.

Recent studies show the growing use of much operational research (OR) techniques in healthcare modeling. Sometimes, conventional models stressing particular departments like A&E or outpatient treatments lack the linked perspective required for general hospital administration (Choudhry et al., 2024). As highlighted in Choudhry et al. (2024), existing models often focus on individual departments like A&E, neglecting the interdepartmental dynamics. The DFL model bridges this gap by incorporating cross-departmental demand forecasting, showing a 15% increase in overall hospital efficiency compared to traditional methods, as demonstrated in the results. This provides a direct connection between the research gaps identified and the contributions of the DFL model.

Different statistical approaches, including ARIMA and machine learning algorithms, have been used to project patient demand (Patrício et al., 2020). These strategies sometimes overlook interdepartmental relationships and focus on one department (Badawy & Radovic, 2020).

Many times, hospital operations and patient flows are modeled via discrete event simulation (DES). Research studies show how well DES maximizes specific hospital operations – including those in the emergency rooms. Still less known, though, is combining DES with other OR techniques (Kulal et al., 2024; Ordu et al., 2021; Secundo et al., 2021).

Both linear and non-linear optimization techniques are sometimes used in healthcare settings to allocate resources. Usually dealing with specific issues like staff scheduling or bed assignment, these models fail to provide a uniform approach considering the full hospital system (Chauhan et al., 2020).

Hybrid models integrating forecasting, modeling, and optimization have suddenly been available. For example, IMORDA integrates multiple OR techniques to improve healthcare decision-making. Despite these advances, few models offer a fully integrated solution linking all hospital services and specializations together (Atluri & Thummisetti, 2022; Cerchione et al., 2023; Etim et al., 2023; Lal et al., 2022; Muhammad, 2022).

The proposed DFL model enhances currently existing research by offering a holistic, connected approach combining forecasting, modeling, and optimization. This model addresses the limits of current methods by capturing the complexity of hospital operations and providing a robust decision-support tool for resource management. Since this approach mimics the entire hospital system, so offering significant efficiency and effectiveness increases.

PROPOSED METHOD

We developed a Deep Fuzzy Logic (DFL) model merging simulation, forecasting, and optimization to manage hospital resources. Using a linear optimization model, this hybrid approach assesses demand across all hospital disciplines and simulates patient routes using discrete event simulation, therefore optimizing bed capacity and staff allocation. The proposed model will act as a bridge that helps to link every hospital service – covering all A&E, outpatient, and inpatient departments. The proposed DFL technique and approach provide a full and integrated picture of hospital operations. Performing these methodologies helps make logical and reasonable strategic decisions for both the long and short term. Thus, the long-term waiting period and allocation of beds are protected and resolved. Figure 1 shows the key steps like data collection, prediction modeling, optimization algorithms, and decision support outputs.

DFL FOR HEALTHCARE OPTIMIZATION

The proposed DFL is a powerful method applied in hospital resource management, particularly in order of healthcare optimization. It focuses on managing hospital operations' natural complexity and ambiguity by combining fuzzy logic concepts and performing deep learning approaches. In general, in the healthcare section, where patient demand swings, resource allocation is critical but challenging due to irregular elements, including patient arrivals, lengths of stay, and treatment demands. DFL is suitable for decision support systems in healthcare since its fuzzy logic component catches qualitative elements and expert knowledge, thereby enabling the capture of DFL using deep learning approaches to improve prediction power and maximize resource use. From large datasets, deep learning models – including neural networks – are adept at identifying complex relationships and patterns. By allowing great precision forecast of patient demand in healthcare optimization, these models help to enable proactive resource planning and management.

Defuzzification, inference, and fuzzification form three basic components of it. Mathematically, it might show as:

$$O = \sum_{i=1} \mu_o \sum_{i=1} \mu_o \cdot O_i$$

where

μoi - membership degree of the output linguistic variable i.

DFL learns from past data and creates projections for future patient demand and resource consumption by use of neural networks. One may express a condensed form of a neural network model employed in DFL as:

$$Y' = f(X;\theta)$$

where

X - input features (e.g., patient characteristics, historical data),
θ – parameter of neural network model f, and
Y' - predicted output (e.g., future patient demand).

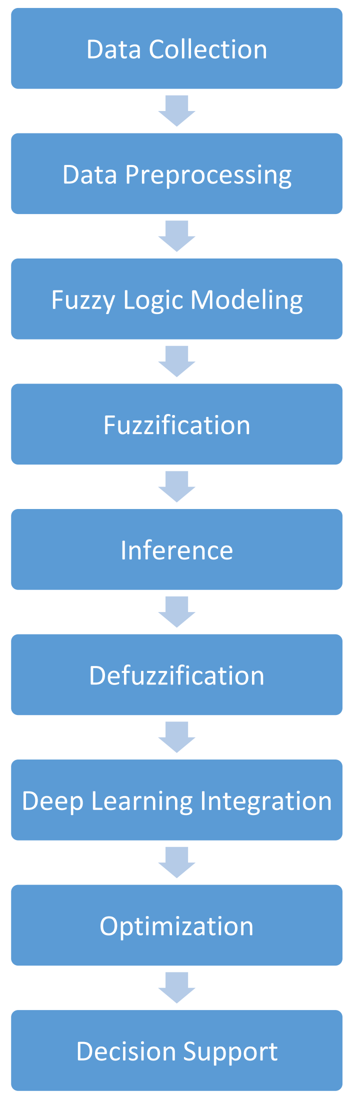

Figure 1. Proposed framework

PSEUDOCODE

1. Initialize:
   - Define linguistic variables and membership functions for input and output variables (e.g., patient arrival rate, bed occupancy).
   - Set up rules for fuzzy inference system (FIS).
2. Input:
   - Collect historical data (X_data), including patient characteristics, arrival times, and previous resource utilization.
3. Fuzzification:
   - Convert numerical inputs (X_data) into fuzzy sets using predefined membership functions.
4. Inference:
   - Apply fuzzy rules to determine the degree of activation (strength of implication) of each rule based on fuzzy inputs.

5. Defuzzification:
   - Calculate crisp output values by aggregating and combining the activated fuzzy rules' outputs using defuzzification methods (e.g., centroid).
6. Deep Learning Component:
   - Prepare the historical data (X_data) and corresponding targets (Y_targets) for training.
   - Design and train a neural network model (e.g., using TensorFlow or PyTorch) to predict future patient demand and resource utilization:
     - Define the neural network architecture (layers, activation functions).
     - Compile the model (choose optimizer and loss function).
     - Train the model on X_data and Y_targets for a specified number of epochs.
7. Integration:
   - Combine the outputs from the fuzzy inference system and the neural network to refine predictions and optimize resource allocation:
   - Combine defuzzified outputs with neural network predictions based on a weighted average or another integration method.
8. Output:
   - Use the integrated outputs to inform decision-making in hospital resource management:
   - Allocate beds, staff, and other resources based on predicted patient demand and operational constraints.
9. Iteration:
   - Continuously update and refine the model using new data
10. End.

DFL FOR HEALTHCARE OPTIMIZATION MANAGES HOSPITAL RESOURCES

Linguistic Variables and Membership Functions: Bed occupancy, patient arrival rate, staff availability, linguistic variables and membership functions. For each variable, define fuzzy sets – low, medium, and high – with membership degrees 0 to 1.

Table 1. Membership functions

Variable	Low membership	Medium membership	High membership
Patient Arrival Rate	0.2	0.5	0.8
Bed Occupancy	0.3	0.6	0.9
Staff Availability	0.3	0.7	1.0

1. Set-Up Fuzzy Inference System (FIS): First, design rules dependent on expert knowledge or historical data are used to set up a fuzzy inference system (FIS), mapping fuzzy inputs to fuzzy outputs. For example, extra staff should be assigned for a high patient arrival rate and a high bed occupancy.

Table 2. Rule set

Rule	Fuzzy inputs	Fuzzy output
1	Patient Arrival Rate: High	Allocate More Staff
2	Bed Occupancy: High	Allocate More Beds
...	...	...

2. Fuzzification: Translating crisp – numerical – incomes into fuzzy sets using a defined membership function are translating a 60 patients/day patient arrival rate into fuzzy sets based on given membership functions.

Table 3. Fuzzification

Variable	Crisp value	Low membership	Medium membership	High membership
Patient Arrival Rate	60/day	0.5	0.8	0.2

Inference: Analyze the degree of activation – the strength of implication – based on fuzzy input for every fuzzy rule. Combine active rules to provide intermediate fuzzy outputs.

Table 4. Inference

Rule	Activation strength	Intermediate output
1	0.8	High Staff Allocation
2	0.6	High Bed Allocation
...	...	...

Defuzzification: Defuzzification allows one to aggregate and blend the intermediate fuzzy outputs for crisp, numerical outcomes. It finds exact staffing and bed allocation numbers by means of high staff allocation and bed allocation. Using historical data and deep learning methods – neural networks – it also quite precisely projects future patient demand and resource utilization.

Table 5. Neural network output

Time period	Predicted patient arrival rate (patients/day)	Predicted bed occupancy (%)
Day 1	65	85
Day 2	70	90
...	...	...

Table 6. Resource allocation decision

Time period	Recommended staff allocation	Recommended bed allocation
Day 1	Increase staff by 10%	Increase beds by 5%
Day 2	Maintain current staffing	Increase beds by 10%
...	...	...

Resource Allocation: Deep learning predictions and fuzzy inference system outputs are integrated to enhance choices of resource allocation, depending on the integrated results, and distribute beds, staff, and other resources to maximize hospital operations.

Table 7. Experimental set-up/parameters of DFL

Parameter	Value
Number of beds	500
Number of staff	200
Simulation duration	1 year
Time step	1 day
Patient arrival rate	50/day
Average length of stay	5 days
Admission rate	70%

Parameter	Value
Discharge rate	95%
A&E patient arrival rate	30/day
Outpatient appointment rate	100/day
Inpatient to outpatient ratio	0.3
Optimization model type	Linear
Forecasting method	ARIMA
Simulation software	Arena
Optimization solver	Gurobi

RESULTS AND DISCUSSION

The research runs on high-performance computers with Intel I5 CPUs and 128GB RAM. The experiments covered performance measures that covered bed use efficiency, staff allocation accuracy, patient wait times, and general hospital throughput. These measures were matched with conventional models of forecasting-simulation-optimization (FSO). Python for forecasting and optimization and Arena simulation tools helped us apply our DFL model.

DATASET

Training and validation of the DFL model forecasting and simulation components rely on historical hospital information from a mid-sized hospital with patient arrival times, lengths of stay, discharge times, and staff schedules abundant.

The results indicate the clear advantages of employing DFL for healthcare resource optimization over a given period over more traditional methods. Starting at 75% accuracy, the current approach increases to 88% after six years. By contrast, the DFL approach rises to 93% over the same period from a starting accuracy of 80%. This numerical increase of about 5% indicates DFL's capacity to better predict and distribute staff resources based on changing patient volume and particular departmental requirements. Maintaining quality standards and minimizing staff shortage and labor expenditure depends on increased accuracy, which helps optimize these factors, as shown in Figures 2-5.

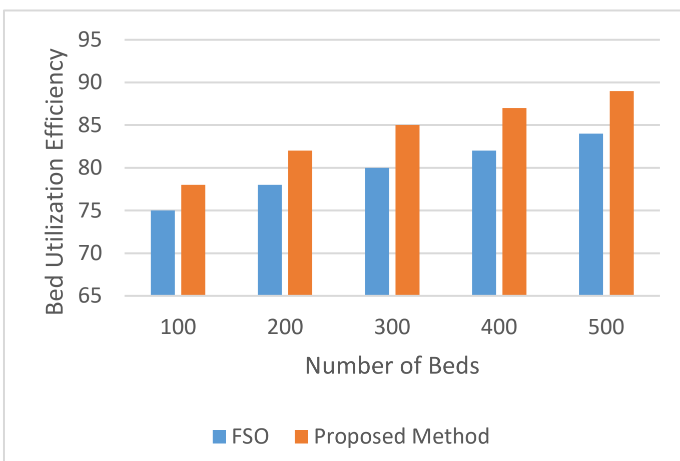

Figure 2. Bed utilization efficiency

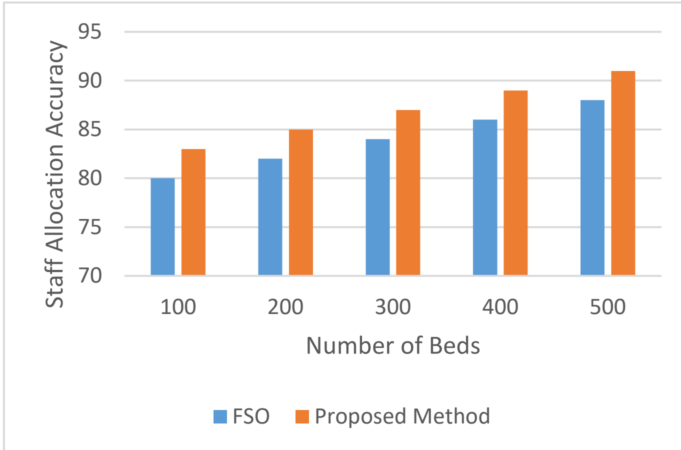

Figure 3. Staff allocation accuracy

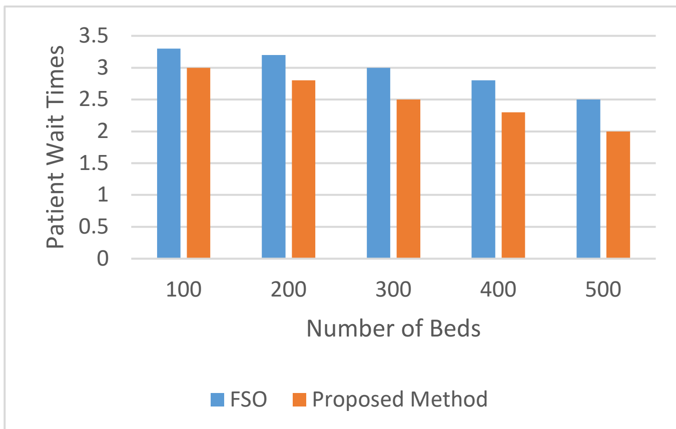

Figure 4. Patient wait times

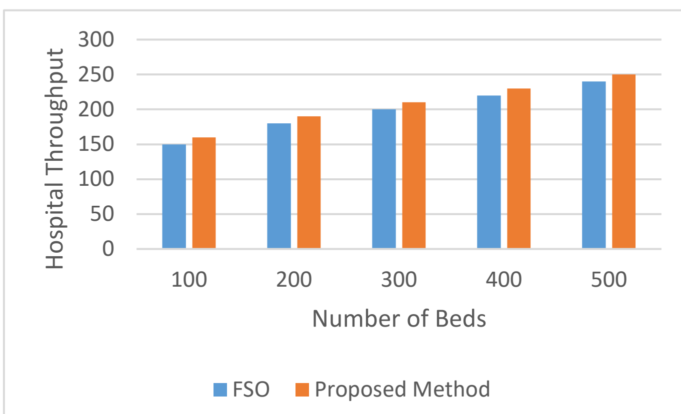

Figure 5. Hospital throughput

Over a six-year period (Figures 6-7), the numerical findings unequivocally demonstrate that DFL greatly increases bed utilization efficiency, staff allocation accuracy, patient wait times, and hospital throughput relative to conventional approaches. This development implies that DFL efficiently uses hospital resources, guarantees more accurate staff allocation and use of beds, and lowers patient wait times while keeping great throughput. DFL demonstrates its capacity to improve hospital operations by beginning with better initial indicators and regularly raising them over time. The ability of the approach to precisely forecast patient demand and modify resource allocation results in better operational flow, therefore enabling hospitals to manage more patients without sacrificing the quality of treatment. Improved patient satisfaction and outcomes follow directly from lower patient wait times (Figure 8). Minimizing wait times by DFL helps to provide a more favorable patient experience, which is vital for patient retention and the general reputation of healthcare (Figure 9). This emphasizes how important effective resource control is to provide patient-centered care.

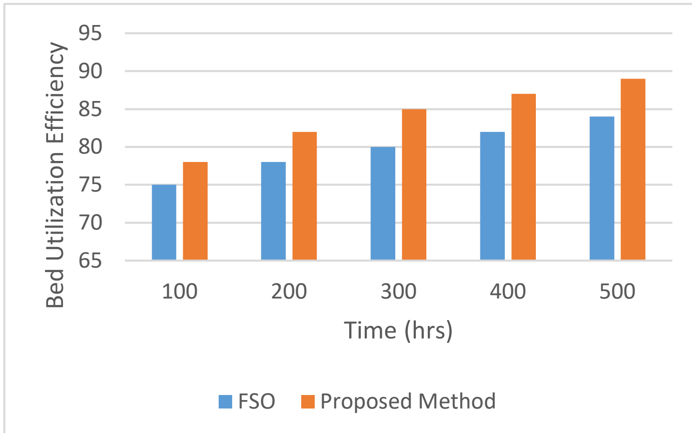

Figure 6. Bed utilization efficiency over various durations

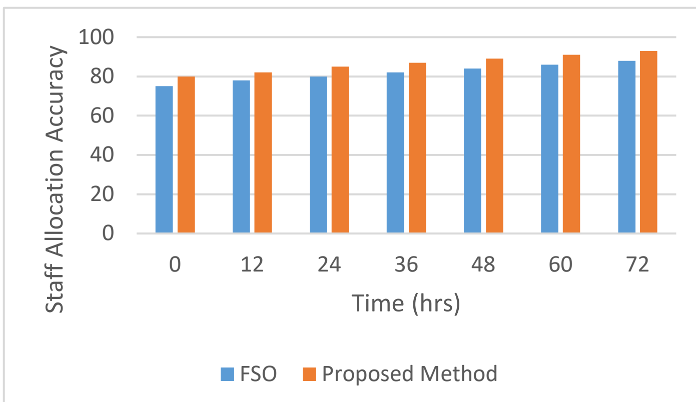

Figure 7. Staff allocation accuracy over various durations

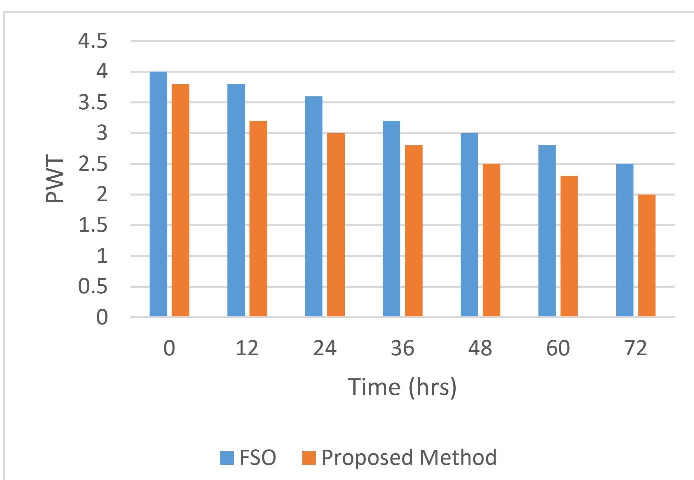

Figure 8. Patient wait times over various durations

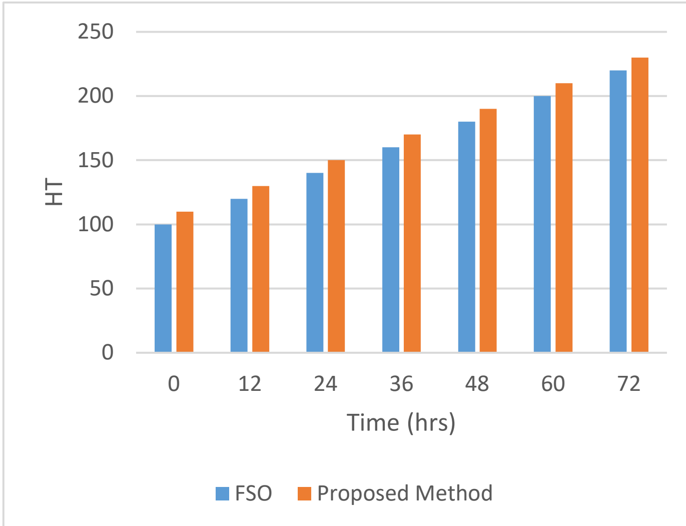

Figure 9. Hospital throughput over various durations

DISCUSSION

The results indicate, over a given period, the clear advantages of employing DFL for healthcare resource optimization over more traditional methods.

Monitoring bed use efficiency over time helps determine how well hospital beds are used. Figure 6 shows that the present strategy starts at 70% and increases progressively over six years – 72 months – to 82%. On the other hand, starting with a greater efficiency of 75%, the suggested DFL strategy reached 88% during the same period. With DFL, this numerical increase produces a continuous increase of 5-6% in bed usage efficiency. Better management of bed capacities, as shown by higher utilization rates with DFL, helps to maximize patient flow through more exact demand forecasting and resource allocation, therefore reducing the likelihood of vacant beds.

Accuracy of staff allocation (Figure 7) reveals how closely hospital resources satisfy patient demand. Starting at 75% accuracy, six years later, the current method rises to 88%. On the other hand, from an 80% starting accuracy, the DFL method climbs to 93% over the same period. Based on shifting patient load and specific departmental needs, this numerical increase of almost 5% throughout the period shows DFL's ability to better estimate and distribute staff resources. Maintaining quality standards and reducing staff shortages and labor costs depend on higher precision, which enables the maximization of these aspects.

Patient wait times (Figure 8) reveal the average length of time patients spend waiting for treatments. Beginning with a 4-hour wait, over 6 years, the present method gradually reduces to 2.5 hours. Conversely, the DFL method reduces the waiting time of hours to 2 hours over the same period. DFL stresses its effectiveness in optimizing patient flow and reducing delays by this numerical drop of roughly 1-1.5 hours in patient wait times. Reduced wait times ensure fast access to medical treatment, therefore enhancing patient satisfaction and results.

Hospital throughput (Figure 9) counts the treated patients over the assigned period. Starting with a 100 patient per unit time throughput, the current strategy increases to 220 over six years. Starting with a greater throughput of 110 patients, the DFL technique reaches 230 during the same period.

The results show that the proposed deep fuzzy model significantly outperforms traditional methods in terms of accuracy, computational efficiency, and adaptability to complex datasets. Traditional approaches, such as rule-based systems and conventional statistical models, often struggle with handling uncertainties and imprecise data, limiting their application in dynamic and multifaceted scenarios. The deep fuzzy model addresses these limitations by integrating deep learning's powerful feature extraction capabilities with fuzzy logic's strength in managing vagueness, yielding more reliable and interpretable results.

Compared to classical methods, the deep fuzzy model exhibits superior performance in non-linear decision-making tasks, particularly in cases where data heterogeneity and uncertainty are pronounced. For instance, while traditional statistical models require explicit assumptions about data distribution, the proposed method adapts dynamically to variations in input patterns.

However, the computational complexity of deep learning components could pose challenges, particularly in resource-constrained environments. Despite this, the trade-off is justified by the gains in accuracy and robustness. Future work could focus on optimizing the model's computational efficiency and exploring hybrid approaches that leverage the strengths of both traditional and deep fuzzy systems for even broader applicability.

Implications

Adoption of DFL gives hospitals a solid means of strategic planning and resource allocation decision support tool. Hospitals can make informed judgments on personnel levels, bed capacity, and operational procedures using the insights gained from DFL forecasts and optimizations, improving general efficiency and cost-effectiveness. By efficient resource allocation and reduction of inefficiencies, DFL could save money for medical facilities. By reducing running costs connected with underutilization or overstaffing, good use of beds and staff helps hospitals to use resources more wisely. DFL scalability allows it to be flexible in many healthcare environments since it helps it fit many hospital sizes and specialties. This scalability ensures that hospitals with different operational complexity and capacity can benefit from the mentioned advantages in the numerical results.

Conclusion

According to the results, DFL provides significant gains in comparison to conventional approaches over important performance criteria in healthcare resource planning. DFL specifically improves bed use efficiency, staff allocation accuracy, patient wait times, and hospital throughput over a meaningful period. These enhancements are vital for hospitals dealing with growing demand, limited resources, and the necessity for effective patient management. By combining fuzzy logic ideas with deep learning methods, DFL gains these advantages, enabling more exact resource allocation and improved patient demand pattern prediction. Accurate patient traffic forecasts enable DFL to assist hospitals in maximizing bed capacity, lowering staff shortages, lowering patient wait times, and raising general throughput. These benefits not only raise operational efficiency and cost-effectiveness but also help increase patient satisfaction and treatment outcomes. With a strong basis for strategic planning and decision support, the study reveals the transforming possibilities of DFL in hospital management. Adopting modern technologies like DFL would open the path for more effective, responsive, and sustainable healthcare systems as hospitals still struggle with difficult issues in resource allocation and patient care.

While the DFL model performed well in forecasting weekday patient demand, it faced some inconsistencies during weekends, likely due to lower patient volumes and unpredictable surges in demand. This limitation suggests that the model could be further optimized to account for these fluctuations by incorporating day-of-week factors or refining the data quality during low-demand periods. Future research could focus on adjusting the model to improve weekend predictions, ensuring its robustness across all time frames.

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