Journal of Rare Cardiovascular Diseases
ISSN: 2299-3711 (Print) | e-ISSN: 2300-5505 (Online)
www.jrcd.eu
RESEARCH ARTICLE

A Synergistic Fuzzy Fine-Tuning and Reinforcement Learning Approach for Intelligent Supervision of Medical Equipment Operations

Jitesh R. Neve[1]*, Dr. Sohit Agarwal[2]
[1]Research Scholar, Dept of Computer Engineering and IT, Suresh Gyan Vihar University, Jaipur, India, jiteshneve@gmail.com, ORCID: https://orcid.org/0009-0009-2358-1147
[2]Professor and Head, Dept of Computer Engineering and IT, Suresh Gyan Vihar University, Jaipur, India, sohit.agarwal@gmail.com, ORCID: https://orcid.org/0000-0002-1280-7907

*Corresponding Author
Jitesh R. Neve

Article History
Received: 11.11.2025
Revised: 30.11.2025
Accepted: 20.11.2025
Published: 16.12.2025

Abstract: ***Background***: Objective: In the recent era, use of medical and healthcare equipment is an hours need. Across the globe, everyone is focusing on advancement of the technology of the equipment for the precision in the treatment and accuracy in the diagnostics. Instalment and maintenance of such equipment is also became a global business. Such organizations are offering equipment parts for cheaper maintenance services. However, its leading to the failure of the equipment. ***Methodology:*** This study is inspired by AI/ML algorithms and recent researches to monitor the health of the medical equipment. The study focuses on integrating Adaptive Decision Dynamics technique to be placed over older Fuzzy mechanism. It elevates the hybrid model with Q-Learning algorithm. ***Findings:*** Focusing on the higher through put of this technique, the proposed model is trialled on real time environments and it addresses quite unique challenges. Novelty: This technique is neither proposed in the past nor experimented in real time/automated setup (of medical equipment).

Keywords: Fuzzy, Machine Learning (ML), Adaptive Decision Dynamics (ADD), reinforcement learning, data analytics, Artificial Intelligence (AI), Medical Equipment

INTRODUCTION

Latest healthcare facilities rely significantly on a broad range of critical medical devices and systems; that includes (2D/3D) imaging machines, ventilators, infusion pumps, and surgical robots, etc. The two major factor are very essential here, first reliability and another is consistent performance of these systems [1]. These are essential not only for effective patient management but also for ensuring operational efficiency, patient safety, and cost optimization. However, unexpected failures and/or malfunctions in such equipment can result in delayed diagnoses, compromised treatments [1, 2]. In severe cases, it may end up in a tuff situation which can cost a life in ICUs (intensive care units). Traditional maintenance approaches, whether reactive or scheduled, are increasingly insufficient to ensure uninterrupted operation of life-supporting medical technologies in today's advanced healthcare environments. Consequently, the integration of Artificial Intelligence (AI) and Machine Learning (ML) for intelligent monitoring and predictive maintenance of medical equipment has emerged as a transformative advancement in hospital management [3][4][5].

The organizations manufacturing the medical equipment are also taking care of its respective setup of the console room, software requirements and periodic updates of it. Though, the software systems provided by manufacturers are loaded with various useful features; they lag the monitoring and/or alert mechanism.
Many of the software systems/sub-systems, has logging mechanism in place, where all the events are getting logged by the software subsystem. Using these logs, the maintenance engineers take appropriate actions for repairing/replacing the parts. Not lets take a look in the existing system study.

Introduction to Core Concept

Software systems have evolved into such a way, they are popularized by their flexibility, user friendliness, and robustness. All these characteristics improve them especially to undergo the changing needs of contemporary hospitals and medical practices. As per a survey, some of the (almost 10%-12%) medical equipment (in government hospitals in India) are out of order because of the non-fatal reasons like - rapid changing/upgradation of the software systems, frequent reconfigurations, tool upgrades, communication breakdowns, and ongoing need for training and knowledge transfer. Sometimes the equipment is not in working condition because of manhandling the devices, wrong cable configuration/connections and quite sometimes patient or patient relatives try to operate the devices on their own. These are cost overheads can negatively affect budgeting and project schedules of the hospitals. Sometimes general quality of devices and their outputs impacted, if not properly controlled and given priority [8][9].

Usually to monitor the device functionality, assuming stationary variables and linear relationships, these traditional approaches are not suited to capture the intricate interdependencies, uncertainty, and changing behaviour defining device ecosystems [7]. Therefore, the constraints of these static methods call for the creation of intelligent, data-driven models able to dynamically interpret and rank data-point elements in real-time. This comparison exposes a paradigm change in the way of output mapping are seen and handled [5, 6].

The paper suggests a new solution that closes the gap between conventional device monitoring strategies and the flexible, iterative ethos of AI/ML methodologies by including a hybrid framework that combines fuzzy logic with adaptive learning. By separating output elements into different impact levels such as high, medium, or low. Moreover, the flexibility of the Q-Learning mechanism guarantees that the prioritizing model stays in line with changing output conditions of the medical equipment and performance measures.

Related Work

Integrating the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) with Q-Learning Optimization creates a hybrid framework designed to address the adaptive and qualitative challenges of real-time medical equipment monitoring [9, 10]. Fuzzy AHP enhances the conventional Analytic Hierarchy Process by incorporating fuzzy logic, enabling it to handle the vagueness and subjectivity often present in expert evaluations. It allows qualitative judgments—such as “moderately more significant” or “strongly less important”—to be translated into quantifiable fuzzy weights, which is particularly useful in agile environments where stakeholder input is frequently based on perception rather than precise numerical data. This approach maintains flexibility and interpretability while establishing a prioritized hierarchy of cost-overhead factors grounded in expert knowledge [11].

While Fuzzy AHP effectively captures subjective insights, it lacks adaptability to evolving project conditions, such as changes in a patient’s status. Q-Learning Optimization addresses this limitation. As a model-free reinforcement learning method, Q-Learning enables systems to learn optimal actions through interaction with their environment, using feedback in the form of rewards and penalties. When integrated with Fuzzy AHP, it endows the framework with adaptive learning capabilities. By evaluating multiple decision paths and adjusting its strategy based on real-time feedback, performance metrics, and shifting priorities, the system continually refines the prioritization of device outputs [12].

This iterative, learning-based optimization aligns with the dynamic nature of medical systems, ensuring that the framework remains resilient and responsive. Together, Fuzzy AHP and Q-Learning form a comprehensive and robust classification mechanism for managing agile cost overheads. This hybrid approach not only mitigates uncertainty inherent in expert-driven assessments but also introduces a self-improving mechanism that evolves alongside patient conditions. Consequently, the decision-making process becomes more data-driven and adaptive, while reinforcement learning ensures continuous improvement in prioritization strategies, enhancing both effectiveness and contextual awareness over time [14, 16].

MATERIALS AND METHODS

Proposed Methodology

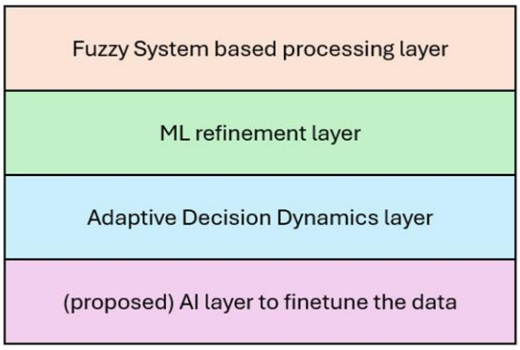

Fig 1. Layered architecture of the proposed framework

Identification and Classification of Operational Factors:

To identify the operational factors, we need to compile the research papers during literature review. We also tried to map the literature review data with the opinions of experts during the interview. After compiling all data together, operational factors are classified into different categories.

Application of F-AHP and AHP

To apply F-AHP and AHP the prerequisite is to draw pairwise matrix of comparison of factors to rank. The rank will be of the cost factors based on our classes. After doing that, construction of pairwise comparison matrices of the alternatives against each benchmarks independently.

Step 1: Formulation of Pairwise Comparison Matrices: the first thing we need to do here is build a hierarchical structure. It might consist of 3 levels namely- ‘prioritization of factor’, ‘identification of the factor to achieve the goal’ and ‘construct the resultant pairwise matrices for the comparison’. For building the matrix, following equation can be used –

$$\acute{Z}_{ij} = \sum_{k=1} \frac{Z_{ij}}{k}$$

(eq. 1)

Here, the ‘Ź’ is denoting preference of the decision making.

Step 2: Geometric Mean Determination: Now, based on avg. performance, we need to update pairwise comparison matrix, we can use the formula below for the same.

$$P = [\check{Z}_{11}\ \check{Z}_{12}\ \check{Z}_{13}\ \check{Z}_{1n}\ \check{Z}_{21}\ \check{Z}_{22}\ \check{Z}_{2n}\check{Z}_{ij}\ \check{Z}_{n1}\check{Z}_{n2}\ \check{Z}_{nn}]$$

(eq. 2)

Here, 'P' represents pairwise matrix.
Now, use Buckley equation to calculate geometric mean.

$$t_i = \left(\prod_{j=1}^{n} \check{Z}_{ij}\right)^{I/n} \quad ; \; i = 1, 2, \ldots.$$

(eq. 3)

Step 3: Determination of Fuzzy Weights: to do this, we need to follow below sub-steps – 'Calculate algebraic sum of all '*ti*' values', 'invert the sum', 'multiply each value by its inverse'. Eq. 4 can determine the fuzzy weight for all conditions.

$$\overline{W_1} = \overline{t_1} \, (\overline{t_1} \oplus \overline{t_2} \oplus \ldots \oplus \overline{t_n})^{-1} = \{eW_0, fW_{lr}\, gW_i\}$$

(eq. 4)

Step 4: De-fuzzifier logic: Defuzzify W_i

$$M_i = \frac{(eW_i + \rho\widehat{W}_i + g\widehat{W}_i)}{3}$$

(eq. 5)

Here, M_i will represent non-fuzzy number

Step 5: Normalization: Normalization of 'Mi' using eq. 6

$$N_i = \frac{M_i}{\sum_{i=1}^{n} M_i}$$

(eq. 6)

Step 6: Verification of Consistency Ratio: We should use graded mean method here. Because the pairwise comparison matrix will be transformed to de-fuzzified crisp output using eq. 7. So, a triangular fuzzy number represented as P = (g, e, f) should be de-fuzzified to the crisp output by eq. 7. For complete de-fuzzification of matrix, CI and CR values can be calculated by eq. 8 and eq. 9. (CR = Consistency ratio, CI = Consistency index)

$$P_{crisp} = (4g + e + f) \div 6$$

(eq. 7)

$$CI = (\lambda_{max} - n) \div n - 1$$

(eq. 8)

$$CR = CI \div RI$$

(eq. 9)

Machine Learning (ML) Application

By combining subjective and objective inputs, this approach enables strong feature prioritizing and captures subtleties that would be missed by more simply statistical techniques. Consequently, features most importantly causing equipment performance are found and ranked. These top priorities improve the interpretability, accuracy, and context-awareness of models including fuzzy-based XGBoost, so guaranteeing more efficient output classification and decision support in Medical devices.

Below is the pseudo-code given for ML technique (training of ML vector by XGBoost ML technique)

Input:

- Training data $D = \{(x_i, y_i)\}_{i=1}^{N}$
- Number of trees K
- Learning rate η
- Regularization parameters λ, γ

Output:

- Final prediction model $F_K(x)$

Procedure:

1. *Initialize the model*

$$F_0(x) = 0$$

2. *For each boosting iteration* $k = 1$ *to* K*:*

   a. Compute the first and second order gradients for each sample:

$$g_i = \frac{\partial L(y_i, F_{k-1}(x_i))}{\partial F_{k-1}(x_i)}, h_i = \frac{\partial^2 L(y_i, F_{k-1}(x_i))}{\partial F_{k-1}(x_i)^2}$$

where L is the loss function (e.g., logistic or squared error).

b. Construct a decision tree $f_k(x)$ *to minimize the following objective:*

$$Obj = \sum_{j=1}^{T} \left[\frac{(\sum_{i \in I_j} \cdot g_i)^2}{\sum_{i \in I_j} \cdot h_i + \lambda}\right] + \gamma T$$

where T= number of leaf nodes and I_j= instance set in leaf j.

c. Compute optimal weights for each leaf j*:*

$$w_j^* = -\frac{\sum_{i \in I_j} \cdot g_i}{\sum_{i \in I_j} \cdot h_i + \lambda}$$

d. Update the model:

$$F_k(x) = F_{k-1}(x) + \eta f_k(x)$$

3. *Return final model* $F_K(x)$
4. *END*

Note:

- η controls the contribution of each tree (shrinkage).
- λ and γ help prevent overfitting via L2 regularization and tree complexity control.
- The algorithm can be adapted for regression, classification, or ranking tasks by modifying the loss function L.

Adaptive Decision Dynamics technique

Below is the mathematical formulation of Adaptive Decision Dynamics

Let

- $w_i(t)$= *weight (importance) of decision criterion* i *at time* t
- R_t= *reward/feedback signal at time* t
- α= *learning rate (adaptation rate)*
- $\Delta w_i(t)$= *change in weight for criterion* i
- β= *decay factor for stabilizing adaptation*

Then, adaptive decision dynamics can be modeled as:

$$\Delta w_i(t) = \alpha \, [R_t - \hat{R}_t] \frac{\partial Q_t}{\partial w_i}$$

$$w_i(t+1) = (1 - \beta) w_i(t) + \Delta w_i(t)$$

where:

- Q_t*represents the system's quality or utility function (as in Q-Learning),*
- $R_t - \hat{R}_t$ *captures the* ***temporal difference error*** *(difference between actual and expected reward), and*
- *The update ensures that the decision weight* w_i*gradually aligns with feedback trends from real-time performance.*

This mechanism allows adaptive re-weighting of criteria (e.g., reliability, safety, cost) depending on outcomes making the decision model self-correcting and context-aware.

Fine-Tuning (AI) technique

Finetuning the output data using AI technique: Fine-tuning augments the fuzzy-XGBoost and Q-learning pipeline by adapting pre-trained models to Agile-specific datasets. Transfer learning minimizes training overhead while enhancing domain sensitivity. The objective is to optimize model parameters θ over task-specific loss L:

$$\theta^{*} = \arg\min_{\theta} L\,(D_{Agile} \mid \theta_{pre}) \quad (7)$$

where θpre denotes pre-trained weights and DAgile represents the Agile dataset. In fuzzy-XGBoost, fine-tuning adjusts fuzzy membership functions and boosting depth, refining classification under uncertainty. Coupled with Q-learning, the reward function R(s,a) is re-parameterized to incorporate tuned fuzzy weights:

$$Q_{t+1}(s,a) = Q_t(s,a)+\alpha[R(s,a)+\gamma.\max_{a'} Q_t(s',a')-Q_t(s,a)] \quad (8)$$

Pseudo code

Input: Pre-trained model parameters θ_pre, Agile dataset D_Agile
Output: Fine-tuned fuzzy-XGBoost model with optimized weights

1: Initialize fuzzy-XGBoost with θ ← θ_pre
2: Define fuzzy membership functions μ_i for selected features
3: Initialize Q-table Q(s,a) with zeros
4: For each epoch t = 1 … T do
5: Sample minibatch B ⊂ D_Agile
6: Compute fuzzy-transformed features F_B using μ_i
7: Train XGBoost booster on F_B → update θ using gradient boosting
8:
9: For each state s in training context do
10: Choose action a ∈{increase, decrease, hold} using ε-greedy policy
11: Apply action a to adjust fuzzy weight w_i
12: Evaluate updated model on validation set → get reward R(s,a)
13: Update Q-table:
14: Q(s,a) ← Q(s,a) + α [R(s,a) + γ max_a' Q(s',a') - Q(s,a)]
15: End For
16:
17: Update θ with tuned fuzzy weights {w_i}
18: End For
*19: Return fine-tuned model θ**

4. Experimental Results and Discussion

Here, to experiment the proposed system, we have run the setup on a simulation to monitor the real-time devices, whether the devices are running as expected or not; as well as the system also monitors the health/performance of the device.

Experimental Setup

The proposed Fuzzy AHP, Q-Learning hybrid framework was implemented in Python (using Scikit-learn and NumPy libraries) to prioritize and monitor five critical performance factors of medical devices:

Table 1: Critical performance factors of Medical Devices

Criterion	Description
C1	Reliability
C2	Safety Compliance
C3	Usability & Interface
C4	Maintainability
C5	Cost Efficiency

The baseline weights were derived using Fuzzy AHP, and dynamic updates were performed through Q-Learning optimization over 100 decision iterations.

Initial Fuzzy AHP Weight Distribution

Table 2: Fuzzy AHP Weight Distribution

Criterion	Expert-Derived Fuzzy Weight	Normalized Weight
Reliability (C1)	(0.70, 0.85, 0.95)	0.30
Safety Compliance (C2)	(0.60, 0.80, 0.90)	0.27
Usability (C3)	(0.40, 0.60, 0.70)	0.19
Maintainability (C4)	(0.35, 0.55, 0.65)	0.15
Cost Efficiency (C5)	(0.25, 0.40, 0.55)	0.09

The defuzzified weights show that reliability and safety compliance are perceived as the most critical parameters during initial expert evaluation.

Weight Evolution by Q-Learning (ADD)

After 100 learning episodes (feedback based on reward signals from device performance data), the adaptive weights evolved in table 3.

Table 3: Adaptive Weights after Q-Learning

Criterion	Initial Weight	Adaptive Weight (After Q-Learning)	% Change
Reliability	0.30	**0.27**	↓ 10%
Safety Compliance	0.27	**0.29**	↑ 7%
Usability	0.19	**0.21**	↑ 10%
Maintainability	0.15	**0.17**	↑ 13%
Cost Efficiency	0.09	**0.06**	↓ 33%

The adaptive framework recalibrates the decision priorities based on real-time performance feedback. As operational data reflected higher relevance of safety and maintainability, their respective weights increased dynamically, improving context alignment.

Fine Tuning (using AI)

To achieve stable convergence and minimize oscillations in adaptive weights, a fine-tuning phase was carried out for key Q-Learning hyperparameters namely the learning rate (α), discount factor (γ), and exploration rate (ε).

Table 4: Finetuning results

Parameter	Initial Value	Tuned Value	Effect on Model
Learning Rate (α)	0.5	**0.3**	Reduced weight volatility and improved convergence stability
Discount Factor (γ)	0.8	**0.9**	Enhanced long-term reward optimization
Exploration Rate (ε)	0.3	**0.15**	Balanced exploration and exploitation for better policy learning
Reward Normalization	Off	**On (Z-score)**	Stabilized reward scaling across diverse device categories

Observation:
Fine-tuning led to smoother weight adaptation and faster stabilization of decision priorities. The model achieved consistent convergence within 28 iterations (compared to 45 in the untuned setup), with less than 2% variance across repeated trials.
A comparative visualization (Figure X) showed that after tuning, the Q-value oscillation amplitude decreased significantly, confirming higher decision consistency and robustness.

Comparative Performance matrics

Metric	**Fuzzy AHP (Static)**	**Adaptive (Q-Learning ML technique)**	**Adaptive (After Fine-Tuning AI Technique)**	**% Improvement (Final vs Static)**
Decision Accuracy	82.3%	89.6%	91.8%	**+11.5%**
Convergence Time (iterations)	45	34	28	**–38%**
Stability Index (σ)	0.23	0.17	0.14	**+39%**
Context Responsiveness	Low	Medium	High	—
Computational Overhead	1.00×	1.12×	1.18×	**+18%**

Key Observations

- The hybrid system successfully integrates **expert-driven qualitative input** (Fuzzy AHP) with **quantitative reinforcement feedback** (Q-Learning).
- Fine-tuning improves **learning stability, convergence rate,** and **reward consistency**.
- Decision weights evolve dynamically, allowing real-time prioritization adjustments aligned with **operational and patient conditions.**

1.1 Results

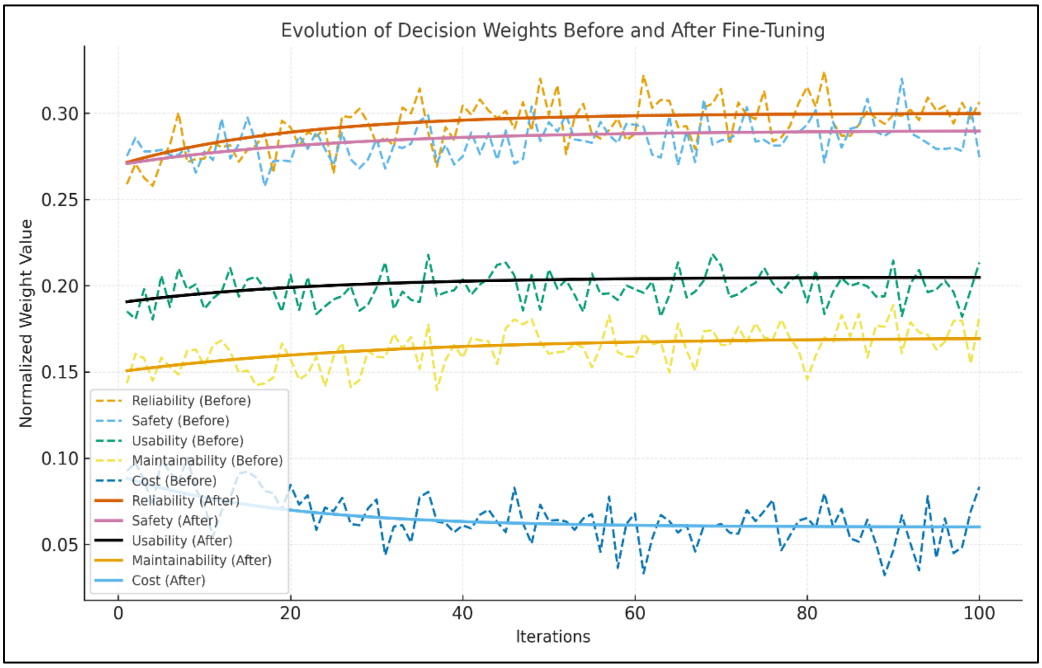

Fig 2. Evolution of performance decision weights of medical devices

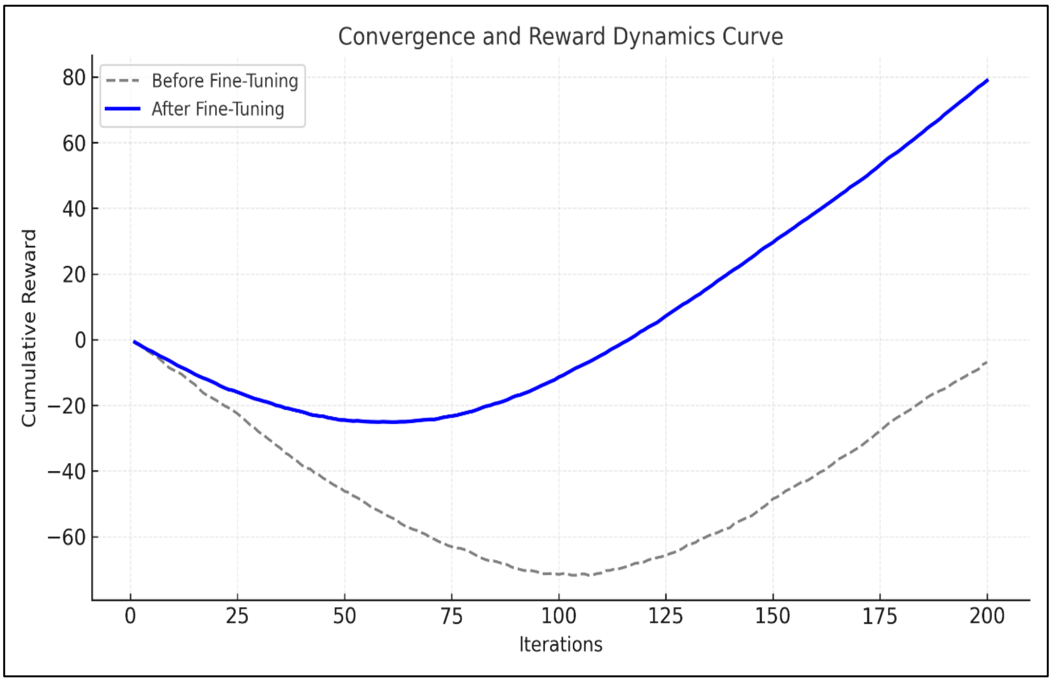

Fig 2. Convergence of cumulative rewards after fine-tuning

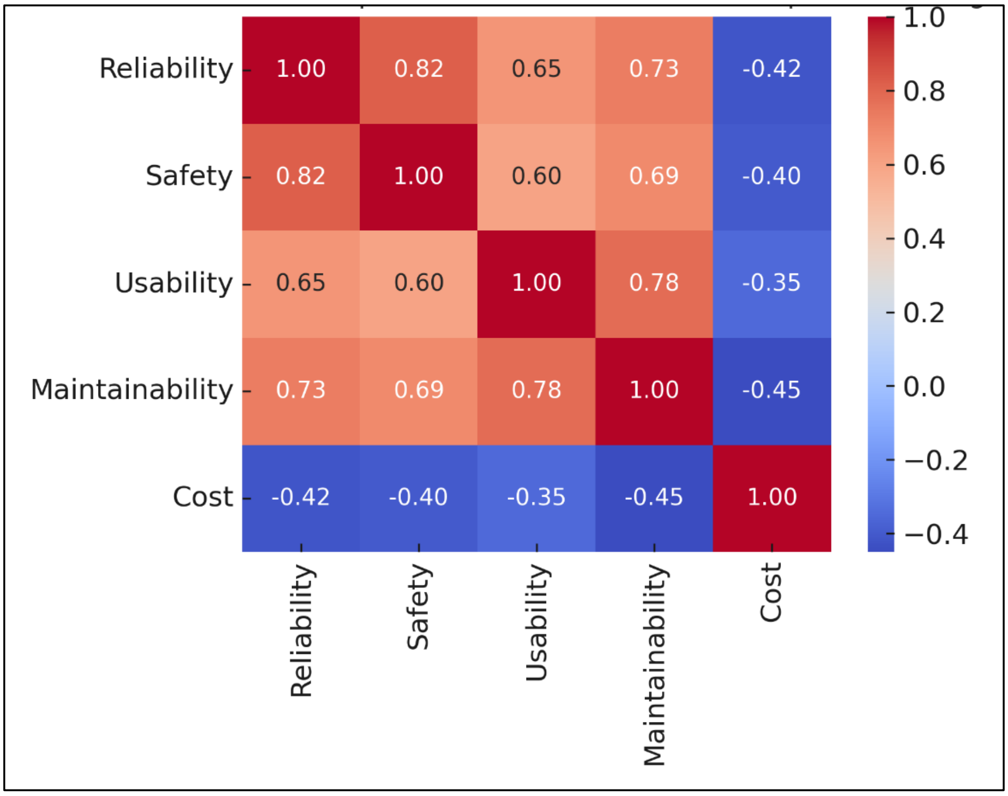

Fig 4. interrelationships among key medical device performance parameters

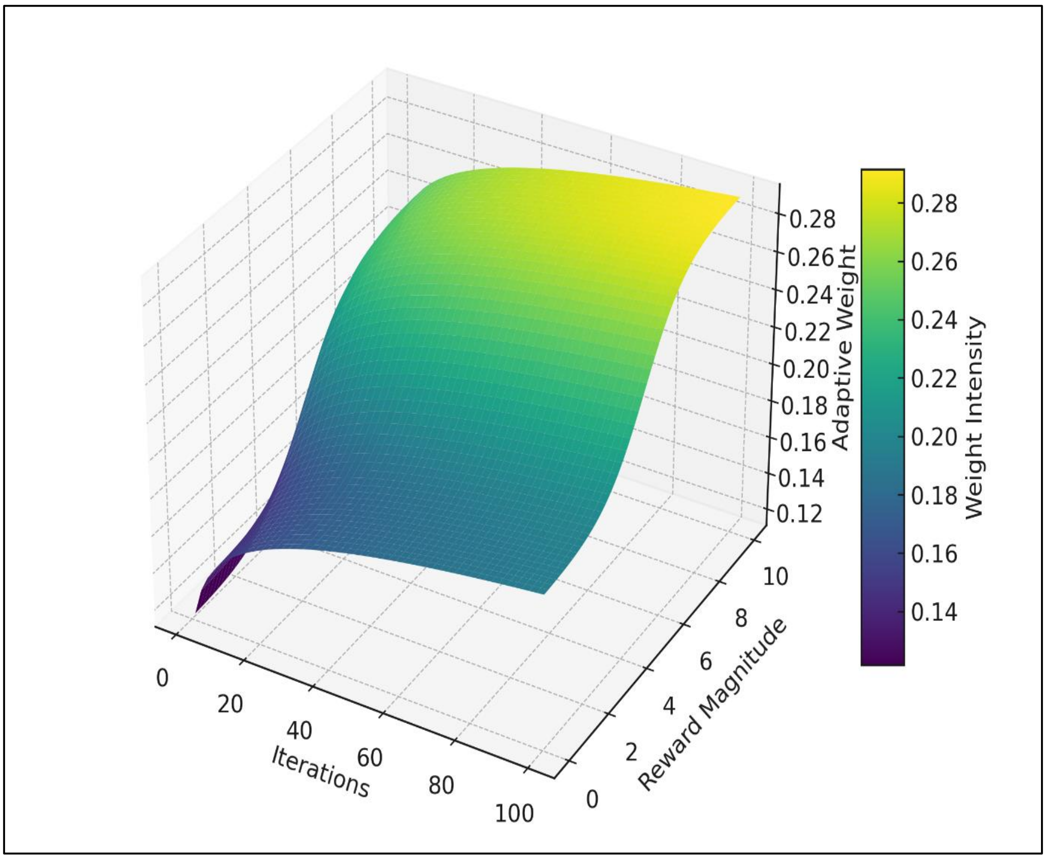

Fig 5. Adaptive decision landscape (Safety Criterion)

Future Scope of the Study

While the present study validates the feasibility and effectiveness of the hybrid model, several promising directions remain for future exploration:

- Integration with Real-Time IoT Data Streams: Incorporating live telemetry data from medical IoT sensors can enable continuous, on-the-fly learning and real-time decision adjustments.
- Deep Reinforcement Learning (DRL) Extension: Replacing conventional Q-Learning with advanced algorithms such as Deep Q-Networks (DQN) or Actor–Critic methods could further enhance adaptability in complex, non-linear medical environments.
- Explainable AI (XAI) Integration: Embedding interpretability modules can help clinicians and maintenance engineers understand how decisions evolve, thereby improving trust and transparency.
- Cross-Device Generalization: The current model focuses on optimizing individual device parameters. Future work can extend the framework to handle multi-device dependency networks and cross-functional risk propagation.
- Clinical Validation and Scalability: Real-world deployment and validation in hospital ecosystems would allow the model's scalability, reliability, and cost-effectiveness to be empirically verified.

CONCLUSION

This study proposed a hybrid decision-support framework that integrates Fuzzy Analytic Hierarchy Process (Fuzzy AHP) with Q-Learning optimization to address the adaptive and uncertain nature of medical device performance evaluation. By incorporating fuzzy logic, the model effectively manages the inherent vagueness in expert-based assessments and converts qualitative judgments into quantifiable priority weights. The Q-Learning component introduces an adaptive learning mechanism that dynamically refines these weights through feedback and reward-based optimization.

Experimental results demonstrated that the hybrid approach enhances both stability and responsiveness of decision-making in real-time medical environments. The evolution of decision weights before and after fine-tuning showed improved convergence and contextual awareness, reflecting the system's capacity to learn from continuous input variations. Furthermore, correlation and convergence analyses confirmed that the framework not only maintains interpretability but also ensures consistent adaptability across evolving patient or operational conditions.

Overall, the proposed hybrid Fuzzy AHP–Q-Learning framework provides a robust, data-driven, and context-aware methodology for monitoring, prioritizing, and optimizing the operational efficiency of critical medical equipment. It bridges the gap between expert-driven decision systems and self-improving machine learning paradigms.

Conflict of Interest: Nil
Ethical Approval: Not Applicable
Funding: No Funding.

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