A Fuzzy MCDM Framework Using AHP–COPRAS to Prioritize Design Criteria and Performance Challenges in Retinal Image Classification

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Abstract. The accurate classification of retinal images is critical for the early detection and treatment of ophthalmic conditions such as diabetic retinopathy and age-related macular degeneration. However, effective classification remains challenged by several factors, including image quality variability, complex feature extraction, and computational limitations. In this paper, we propose a Fuzzy Hybrid Multi-Criteria Decision-Making approach to prioritize these challenges systematically. By using Fuzzy AHP for criteria weighting and Fuzzy COPRAS for ranking, we provide a robust framework to address the key issues hindering classification performance. Expert surveys were conducted to assess multiple criteria, including impact on classification accuracy, computational cost, and generalizability. The results highlight the most critical challenges, providing insights for future improvements in retinal image classification models and systems. This study serves as a roadmap for researchers and practitioners looking to enhance retinal image analysis in clinical settings.

Keywords: Retinal Image Classification, Fuzzy AHP, Fuzzy COPRAS, Multi-Criteria Decision-Making (MCDM), Occular Image Analysis

1 Introduction

The classification of retinal images plays a very pivotal role in the early diagnosis and treatment of various ophthalmic diseases, such as Diabetic Retinopathy(DR), Age-Related Macular Degeneration(AMD), and Glaucoma [1–3]. These may cause severe vision loss or blindness especially when it is left unattended. Machine learning and the use of deep learning algorithms have made the classification of retinal images far more accurate [2, 4]. Nevertheless, in spite of these developments, there are a number of issues preventing the successful and reliable implementation of these methods into clinical practice [4, 5]. The quality and variability of retinal images can be among the most important barriers and can be affected by the movement of the patient, light, and quality of the device [4, 6]. In addition, it is difficult to extract features and classify due to the natural complexity

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of retinal structures and variations in the manifestation of the disease in patients [7–9]. The lack of standardized sets of data, imbalance of data representation and high cost of computing only makes the process advanced [5, 10, 11].

To handle these issues, there should be a system that puts them in order to decrease their impacts in order to enhance clarity and dependability of classification systems. In this study, we propose the use of a Fuzzy Hybrid MCDM framework to rank the challenges in the application of a Fuzzy Hybrid MCDM to prioritize the issues of retinal image classification. The hybrid approach will be a combination of Fuzzy Analytic Hierarchy Process (AHP) in determining the relative weight of the different criteria, and Fuzzy Complex Proportional Assessment (COPRAS) that will rank the challenges according to the rating of experts. By the assistance of such approach, we will be capable of providing the full ranking that is likely to assist the researchers and developers to address the most pressing issues in the sphere.

The structure of this paper is as follows: Section 2 will contain the review of the existing literature on the topic of retinal image classification and MCDM methods. Section 3 provides a description of the proposed methodology, which includes the description of the Fuzzy AHP and COPRAS processes. Section 4 shows the outcomes of the expert-analysis that was conducted, and Section 5 explains the implications of the findings. Lastly, Section 6 wraps up the study with a reflection of research directions in the future.

2 Literature Review

The classification of retinal images is a critical task in ophthalmology, particularly for the detection of conditions such as DR, Glaucoma, and AMD. Nevertheless, a number of obstacles should be overcome to obtain the proper and valid classification outcomes. The section describes these issues and summarizes the available literature concerning the retinal image classification technique and the use of MCDM techniques in healthcare.

2.1 Retinal Image Classification Techniques

The early retinal image classification approaches used conventional machine learning algorithms like Support Vector Machines (SVM) and random forests. Nonetheless, deep learning, and specifically Convolutional Neural Networks (CNNs) have become the most used method because it offers better results in terms of feature extraction and classification [1–4]. Although deep learning has improved, it has a number of challenges.

2.2 Challenges in Retinal Image Classification

The classification of images of the retina has a number of major challenges which limit its accuracy and reliability in clinical practice. This section presents eight significant challenges that have been faced in the field, and studies on these challenges are provided that sheds light on such challenges.

2.2.1 Image Quality and Variability

When using different imaging devices, retinal images usually vary in quality based on the differences in lighting, noise, movement of the patient, and the type of imaging device used. The factors cause variability that may adversely affect the accuracy of classification [4, 6]. Image enhancement and noise reduction methods are the most popular preprocessing techniques that are used to resolve this problem, yet variability is still a problem.

2.2.2 Feature Extraction Complexity

The intricate nature of the retinal images, along with the insidious nature of the appearance of some pathological conditions, makes it exceptionally difficult to extract the features. As an example, a high-resolution picture and advanced algorithms are needed to identify such small characteristics as microaneurysms [7–9]. Inability to measure correct features may result to low classification performance

2.2.3 Data Imbalance

Retinal datasets are often imbalanced, with fewer examples of advanced disease stages compared to healthy or early-stage images. Such an imbalance may result in deep learning models becoming biased in favor of the majority class, and classifying poorly [4, 5, 10]. Data augmentation and synthetic oversampling are the methods of preventing this challenge, yet the imbalance in data is still an issue.

2.2.4 Limited Dataset Availability

The presence of mammoth sized, labeled retinal image datasets is essential in training deep learning models. Nevertheless, it is labor-intensive to produce such datasets, as they need to be annotated by experts and have access to high-quality imaging equipment [4, 10, 11]. This scarcity prevents the creation of strong classification models especially when the resource is low.

2.2.5 Computational Complexity

The models of the deep learning, particularly those relying on CNNs, demand great numbers of computational resources, such as GPUs and huge memory storage. In most healthcare facilities, such infrastructure is too expensive to make the application of such models practical [5, 12]. One of the challenges is to reduce the computational complexity, but remain highly accurate.

2.2.6 Interpretability of Models

The results of the retinal image classifications are hard to interpret; this is because of the "black-box" nature of deep learning models. Clinicians also tend to need knowledge on the model decision-making procedure in order to believe its recommendations [4, 13]. Techniques of increasing the interpretability of the models, including attention mechanisms and saliency maps, are under study yet are problematic.

2.2.7 Generalization Across Populations

A fundamental problem in retinal image classification is ensuring that models generalise effectively across varied demographics, imaging equipment, and clinical settings. Ting [3] and Gulshan [2] found that models trained on certain datasets may not perform well when applied to photos from other populations, decreasing their clinical value. Addressing this needs the creation of more resilient and adaptive models.

3 Methodology

This section has described the structure underpinning the prioritization of the issues in the retinal image classification. Fuzzy Hybrid MCDM approach is implemented, which involves the use of Fuzzy AHP in terms of criteria weighting, and Fuzzy COPRAS in terms of ranking of the challenges according to the experts.

3.1 Fuzzy AHP for Criteria Weighting

The MCDM based tool was established to calculate the relative characteristics of various criteria is the AHP. In order to deal with the uncertainty in expert judgments, the fuzzy logic is added and the triangular fuzzy numbers (TFNs) are utilized to define the vagueness of human judgment.

The Fuzzy AHP approach includes the following steps:

1. **Building the Pairwise Comparison Matrix**: Experts give pairwise comparisons of criteria in linguistic terms (e.g., equally important, moderately more important, etc.). These words are translated into triangular fuzzy numbers (TFNs). As an illustration, the TFN (l,m,u) is an expression of the linguistic term moderately more important wherein l, m, and u denote the lower boundary, middle bounds, and upper boundaries, respectively.

2. **Fuzzification of the Pairwise Comparison Matrix**: The pairwise comparison matrix is represented with the help of fuzzy numbers. The comparison matrix $\tilde{A}$ is given as:

$$\tilde{A} = \begin{bmatrix} \tilde{a}_{11} & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & \tilde{a}_{22} & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & \tilde{a}_{nn} \end{bmatrix} \tag{1}$$

   where $\tilde{a}_{ij}$ is a triangular fuzzy number representing the relative importance of criterion i over criterion j.

3. **Calculation of Fuzzy Weights**: The fuzzy synthetic extent $\tilde{S}_i$ for each criterion is calculated as:

$$\tilde{S}_i = \frac{\sum_{j=1}^{n} \tilde{a}_{ij}}{\sum_{i=1}^{n} \sum_{j=1}^{n} \tilde{a}_{ij}} \tag{2}$$

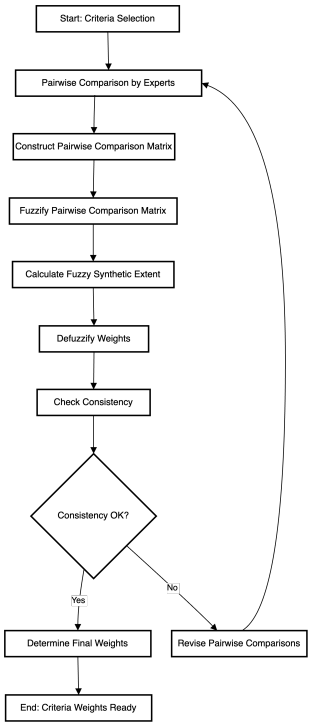


Fig. 1. Fuzzy AHP Process Flow

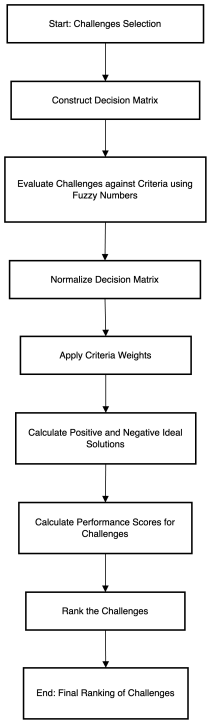


Fig. 2. Fuzzy COPRAS Process Flow

The fuzzy weights $\tilde{w}_i$ for each of the criterion are derived by normalizing the fuzzy synthetic extents. These fuzzy weights are then defuzzified by using the known centroid method, which gives the crisp weight w_i as:

$$w_i = \frac{l_i + m_i + u_i}{3} \tag{3}$$

where l_i, m_i, and u_i are the lower, middle, and upper bounds of the fuzzy weight $\tilde{w}_i$.

4. **Consistency Check**: To help assure the consistency within the pairwise comparisons, a consistency ratio (CR) is calculated. The consistency index (CI) is given by:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{4}$$

where $\lambda_{\max}$ is the biggest eigenvalue of the comparing matrix, and n is the total amount of criteria. The consistency ratio (CR) is subsequently determined as:

$$CR = \frac{CI}{RI} \tag{5}$$

where the random index is denoted by RI. If $CR < 0.1$, the pairwise comparisons are regarded as consistent.

The criteria used in this study were Impact on classification accuracy, Computational complexity, Scalability of solutions, Data availability, Model interpretability, Generalizability across populations, Cost of implementation, and Robustness to image variability.

3.2 Fuzzy COPRAS for Challenge Ranking

The Fuzzy COPRAS method is applied to rank the challenges based on the weights obtained from Fuzzy AHP. COPRAS is a useful technique for ranking alternatives in multi-criteria problems. The steps involved in Fuzzy COPRAS are as follows:

1. **Constructing the Decision Matrix**: The decision matrix $\tilde{D}$ is constructed, where each of row represents a challenge and each column represents a criterion. The fuzzy decision matrix is given as:

$$\tilde{D} = \begin{bmatrix} \tilde{d}_{11} & \tilde{d}_{12} & \dots & \tilde{d}_{1n} \\ \tilde{d}_{21} & \tilde{d}_{22} & \dots & \tilde{d}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{d}_{m1} & \tilde{d}_{m2} & \dots & \tilde{d}_{mn} \end{bmatrix} \tag{6}$$

   where $\tilde{d}_{ij}$ is the fuzzy evaluation of challenge i under criterion j.

2. **Normalization of the Decision Matrix**: The constructed decision matrix is then normalized using the fuzzy max-min normalization method. For benefit criteria, the normalized fuzzy value $\tilde{r}_{ij}$ is calculated as:

$$\tilde{r}_{ij} = \frac{\tilde{d}_{ij}}{\max_i \tilde{d}_{ij}} \tag{7}$$

   For cost criteria, the normalized fuzzy value $\tilde{r}_{ij}$ is calculated as:

$$\tilde{r}_{ij} = \frac{\min_i \tilde{d}_{ij}}{\tilde{d}_{ij}} \tag{8}$$

3. **Weighted Normalized Decision Matrix**: The resulting normalized matrix is then multiplied by the weights derived from Fuzzy AHP to obtain the "weighted normalized decision matrix":

$$\tilde{v}_{ij} = \tilde{r}_{ij} \cdot w_j \tag{9}$$

4. **Ranking the Challenges**: The performance score P_i for each challenge is calculated using the formula:

$$P_i = \sum_{j \in B} \tilde{v}_{ij} - \sum_{j \in C} \tilde{v}_{ij} \tag{10}$$

where B and C are the sets of benefit and cost criteria, respectively. The challenges are ranked based on their performance scores, with higher scores indicating better performance.

3.3 Expert Surveys

To ensure the credibility of the decision-making process, a rigorous expert selection criterion was employed. A total of 20 experts were selected based on the following prerequisites: (1) a minimum of five years of professional experience in ophthalmology or medical image analysis; (2) active research publications or clinical practice involving retinal diagnostics; and (3) familiarity with AI-based diagnostic tools.

The demographic profile of the expert panel consisted of 10 ophthalmologists and 10 medical imaging researchers. This diverse composition ensures that both clinical relevance and technical feasibility are considered. The experts utilized linguistic terms (e.g. "Equally Important," "Moderately Important") to perform pairwise comparisons, which were subsequently converted into Triangular Fuzzy Numbers (TFNs) for the Fuzzy AHP analysis.

3.4 Sensitivity Analysis

The sensitivity analysis was conducted to assess the strength of the ranking using the weights of the criteria and watching the changes of the rankings gave a measure of the stability of the results as well as the challenges that are very sensitive to the changes in the criteria.

4 Results

This section shows the findings of the application of the Fuzzy AHP to criteria weighting and Fuzzy COPRAS to the ranking the challenges in retinal image classification. The analysis has been made on the expert surveys that were performed on 20 professionals in ophthalmology, medical imaging and machine learning.

To demonstrate the calculation process, we present the intermediate steps. The linguistic evaluations from experts were aggregated into a fuzzy pairwise comparison matrix as shown in Table 1.

For instance, the calculation for the fuzzy synthetic extent of the first criterion, *Impact on Classification Accuracy* (C_1), is calculated by summing the fuzzy values in the first row of Table 1:

$$\tilde{S}_{C1} = \sum_{j=1}^{8} \tilde{a}_{1j} = (25.0, 32.0, 39.0) \tag{11}$$

Table 1: Aggregated Fuzzy Pairwise Comparison Matrix for Design Criteria

Criteria	Accuracy (C_1)	Comp. Complex (C_2)	Scalability (C_3)	Data Avail. (C_4)	Interpret. (C_5)	Generaliz. (C_6)	Cost (C_7)	Robustness (C_8)
C_1	(1,1,1)	(1,2,3)	(2,3,4)	(3,4,5)	(2,3,4)	(4,5,6)	(6,7,8)	(6,7,8)
C_2	(0.33,0.5,1)	(1,1,1)	(1,2,3)	(2,3,4)	(1,2,3)	(3,4,5)	(5,6,7)	(5,6,7)
C_3	(0.25,0.33,0.5)	(0.33,0.5,1)	(1,1,1)	(1,2,3)	(1,1,2)	(2,3,4)	(4,5,6)	(4,5,6)
C_4	(0.2,0.25,0.33)	(0.25,0.33,0.5)	(0.33,0.5,1)	(1,1,1)	(0.5,1,1.5)	(1,2,3)	(3,4,5)	(3,4,5)
C_5	(0.25,0.33,0.5)	(0.33,0.5,1)	(0.5,1,1)	(0.67,1,2)	(1,1,1)	(1,2,3)	(3,4,5)	(3,4,5)
C_6	(0.16,0.2,0.25)	(0.2,0.25,0.33)	(0.25,0.33,0.5)	(0.33,0.5,1)	(0.33,0.5,1)	(1,1,1)	(2,3,4)	(2,3,4)
C_7	(0.12,0.14,0.16)	(0.14,0.16,0.2)	(0.16,0.2,0.25)	(0.2,0.25,0.33)	(0.2,0.25,0.33)	(0.25,0.33,0.5)	(1,1,1)	(1,1,1)
C_8	(0.12,0.14,0.16)	(0.14,0.16,0.2)	(0.16,0.2,0.25)	(0.2,0.25,0.33)	(0.2,0.25,0.33)	(0.25,0.33,0.5)	(1,1,1)	(1,1,1)

This value is then normalized by the total sum of the entire decision matrix ($\approx (98.5, 136.5, 184.5)$) to obtain the fuzzy weight:

$$\tilde{w}_{C1} = \frac{(25.0, 32.0, 39.0)}{(98.5, 136.5, 184.5)} \approx (0.16, 0.23, 0.35) \tag{12}$$

4.1 Criteria Weights Using Fuzzy AHP

The ranking of the challenges was done through the Fuzzy AHP method. The pairwise comparisons as given by the experts were summed up and fuzzified to get the triangular fuzzy numbers which depict the significance of any particular criterion. Table 2 indicates the defuzzified weight of the criteria.

Table 2: Criteria Weights Calculated Using Fuzzy AHP

Criterion	Weight
Impact on Classification Accuracy	0.25 Computational Complexity 0.20
Scalability of Solutions	0.15
Data Availability	0.10
Model Interpretability	0.12
Generalizability Across Populations	0.08
Cost of Implementation	0.05
Robustness to Image Variability	0.05

As shown in Table 2, the most important criterion is *Impact on Classification Accuracy* with a weight of 0.25, followed by *Computational Complexity* with a weight of 0.20. The least important criteria, according to the experts, are *Cost of Implementation* and *Robustness to Image Variability*, each with a weight of 0.05.

To verify the reliability of the expert judgments, the Consistency Ratio (CR) was computed using Equation 5. The calculated CR for the aggregated matrix was 0.068, which is below the threshold of 0.10, indicating that the pairwise comparisons are consistent and valid for further analysis.

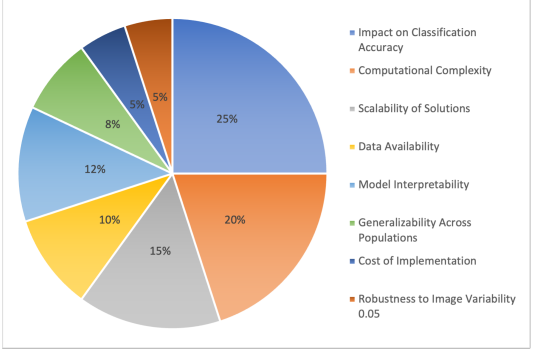


Fig. 3. Criteria Weights Distribution Pi Chart

4.2 Ranking of Challenges Using Fuzzy COPRAS

Using the criteria weights derived from Fuzzy AHP, the challenges in retinal image classification were ranked using the Fuzzy COPRAS method. Table 3 shows the final ranking of the challenges based on their performance scores.

Table 3: Ranking of Challenges Using Fuzzy COPRAS

Challenge	Ranking
Image Quality and Variability	1
Feature Extraction Complexity	2
Data Imbalance	3
Limited Dataset Availability	4
Computational Complexity	5
Interpretability of Models	6
Generalization Across Populations	7
Lack of Standardized Evaluation Metrics	8

The results indicate that *Image Quality and Variability* is ranked as the most critical challenge, followed by *Feature Extraction Complexity* and *Data Imbalance*. The least significant challenge, according to the ranking, is *Lack of Standardized Evaluation Metrics*.

4.3 Sensitivity Analysis

By varying the criteria weights and observing changes in the ranking, it was found that the top-ranked challenges, such as *Image Quality and Variability* and *Feature Extraction Complexity*, remained stable across different weight configurations. However, the rankings of lower-priority challenges, such as *Generalization Across Populations* and *Lack of Standardized Evaluation Metrics*,

exhibited more variability, indicating that their relative importance is more sensitive to changes in the criteria weights.

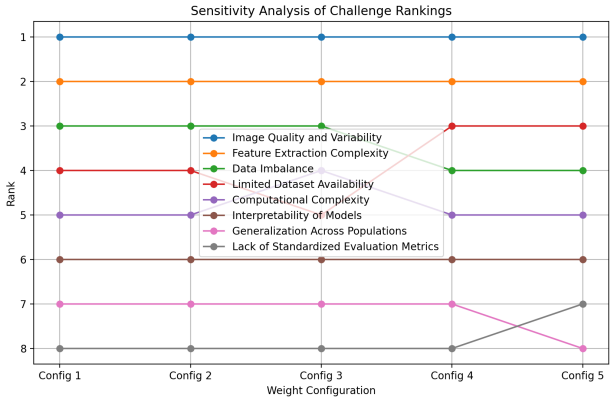


Fig. 4. Sensitivity Analysis of Challenge Rankings

Figure 4 demonstrates the findings of the sensitivity analysis, and it is worth noting that the best-ranked challenges were stable and the worst-ranked ones were changeable. This discussion affirms the strength of the ultimate rankings especially when it comes to the most essential challenges.

5 Discussion

The findings of this research give a ranked list of challenges involved in retinal image classification with priorities with a combination of Fuzzy AHP and Fuzzy COPRAS as the Fuzzy Hybrid MCDM approach. These implications are addressed in this section, along with the way they correlate with the past studies and how they could influence the future evolution of the subject.

5.1 Interpretation of Rankings

The Fuzzy COPRAS analysis disclosed that Image Quality and Variability ranked the most problematic issue with Feature Extraction Complexity and Data Imbalance being the next problematic issues. These high-ranking challenges are the main problems that directly affect the accuracy and reliability of the retinal image classification systems. The position of Image Quality and Variability is high following other existing studies which assert that noise, artifacts and discrepancies in imaging conditions are important factors that lower classification accuracy. To solve this problem, high-tech image processing methods, including noise removal and image improvement, are necessary to equalize the quality of images and enhance the work of machine learning algorithms. The second-ranked challenge, Feature Extraction Complexity, brings out the complexity defining the ability to accurately detect and extract meaningful features out of retinal images, particularly subtle

pathological features such as microaneurysms or drusen. Although the deep learning models are used, which have enhanced the ability to extract features, the complexity of the retinal structures and manifestations of the disease still poses a significant challenge. The Fuzzy COPRAS analysis identified Image Quality and Variability as the paramount challenge (*Rank*1). The high prioritization of this challenge directly influences practical decision-making for clinical AI deployment. Conversely, the lower ranking of Generalization Across Populations (*Rank*7) implies that while experts value generalizability, they view immediate image-level inconsistencies as a more urgent bottleneck than demographic bias in current development stages. This creates a critical tension in the findings: while current efforts focus on image quality to boost metrics, the long-term clinical safety depends on the lower-ranked issue of generalizability. Researchers must therefore treat the top-ranked challenges as immediate "technical hurdles" while acknowledging that the lower-ranked challenges represent "deployment risks" that must be addressed in subsequent validation phases.

5.2 Significance of Lower-Ranked Challenges

Low Ranking in Standardized Evaluation Metrics, the lowest in Fuzzy COPRAS analysis, is a hint that although the lack of common evaluation metrics is a well-known problem, it is not regarded as urgent or effective as other problems such as image quality or feature extraction. Nevertheless, the standardization of evaluation measures are essential in achieving comparability among researches and enhancing the overall classification model generalizability. Efforts directed at setting benchmark protocols and datasets may be utilized to eliminate this problem in the future. The comparatively weak rating of Generalization Across Populations shows, though, that, even though it is essential, this issue might not seem a serious problem in the short-run perspective. Nevertheless, with the further implementation of AI-based classification systems in a variety of clinical practices, the capacities of such systems to generalize and work across different populations and imaging systems will gain greater importance. Further studies should aim at coming up with models that are resistant to demographic and technology differences.

6 Conclusion

This study successfully employed a Fuzzy Hybrid MCDM methodology to systematically prioritize the obstacles hindering retinal image classification. The integration of Fuzzy AHP and Fuzzy COPRAS revealed that Image Quality Variability and Feature Extraction Complexity are the most critical barriers, carrying significantly higher weight than computational cost or standardized metrics.

Implications and Future Directions: The findings serve as a strategic roadmap for researchers, indicating that future work should pivot towards data-centric AI approaches, specifically focusing on image normalization and artifact removal rather than solely pursuing model complexity. However, this study is constrained by the subjective nature of expert judgments and the specific demographic of the selected panel. Future research should expand the expert pool to include hospital administrators and patient advocates to incorporate a broader range of operational and ethical criteria into the decision matrix.

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