Bol. Soc. Paran. Mat.
©SPM – E-ISSN-2175-1188
SPM: www.spm.uem.br/bspm

(3s.) **v. 2026 (44) 2** : 1–9.
ISSN-0037-8712
doi:10.5269/bspm.80467

A Picture Fuzzy Set-Based MADM Framework for Personalized Hospital Recommendations Using Patient Feedback

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ABSTRACT: This paper presents a Picture fyzzy entropy based Multi-Attribute Decision-Making (MADM) approach to generate personalized hospital recommendations from patient feedback. Patient evaluations are modelled using picture fuzzy sets to capture truth, indeterminacy, and falsity. Picture fuzzy entropy is applied to derive objective attribute weights for factors such as infrastructure, staff competency, cost, patient experience, and quality of care. The proposed method produces robust and patient-cantered References hospital rankings, outperforming traditional fuzzy MADM techniques. A real-world case study confirms its effectiveness in supporting data-driven hospital decision-making.

Keywords: Picture fuzzy set, entropy, MADM.

Contents

1. Introduction

The last several decades have seen a tremendous development in the field of quality evaluation over health care, attracting the attention of scholars, politicians, and the general public due to the growing interest in the health business [14,19]. In this regard, new quality metrics are being created daily to evaluate health care services, utilizing the newest technological advancements, such as the emergence of new online social platforms [15]. Patients frequently choose a hospital based on some of the amenities or services they provide. Because of this, knowing how patients view the necessary standard of quality for medical services can benefit both the service provider and the client [3]. As a result, it is critical to pinpoint the main factors influencing the quality of healthcare and concentrate on the traits that patients might find important [26]. Directly asking the recipient about their own experiences is one of the finest ways to learn about the quality of the services. Together with understanding the criteria that hospital patients demand, this is a good and trustworthy indicator of the quality of the services [12]. Nevertheless, it's not always simple or affordable to learn about consumer opinions directly. Therefore, social media sites that allow patients to share their own hospital experiences have developed into an effective informational tool [34]. Domains like topic modeling and opinion mining can assist in making use of the data these platforms offer. Patients are free to express how favorable or unfavorable they feel about the medical treatments in these online reviews. However, they do not necessarily expressly discuss a service in a positive or negative light. It is certain that we may encounter hesitancy or ambiguity in our daily opinions [35]. Any experience can be viewed as a series of events, and not all of the conditions involved have to be either positive or unpleasant; some experiences may have both [22,38].

2020 *Mathematics Subject Classification:* 68T05, 11A55.
Submitted November 29, 2025. Published March 14, 2026

2. Literature Review

Decision-making authorities can identify the best solution among a set of alternatives based on diverse factors through the field of Multi-Criteria Decision-Making (MCDM), a proven area [5,4,11,28,33]. Different methods based on fuzzy logic use fuzzy sets (FSs) or their modifications to define the factors. For instance, Yu et al. used the AHP method to evaluate factors and defined them as FSs and identified the best e-commerce sites based on the TOPSIS method [37]. Kumar et al. used the same method to find the relative weights of the features of smartphones [21]. Dymova et al. presented a model based on the Intuitionistic Fuzzy Set (IFS) together with the TOPSIS method to evaluate the positive and negative opinions of each factor and find the best supplier for a company [13]. Krishnakumar et al. presented the same example of finding the best supplier [20]. A new language-based aggregation (LBA) operator has been proposed to aggregate linguistic terms directly without any conversion. In this approach, alternatives were expressed as IFS-LBA, and PROMETHEE analysis was employed for the ranking process. Afzali et al. [2] presented the construction of the unified decision-making matrix based on the opinions expressed as linguistic variables. These linguistic variables were further represented as interval-form IFSs. Wood et al. [36] presented IFS-TPSIS. In their approach, weights based on entropy were employed. Dahooie et al. [17] used IFS theory for representing the percentage of neutral, negative, and positive opinions about the product. The weights of the importance factors were measured based on the IFS-ICOCW approach. The final ranking results were achieved based on the IFS-MULTIMOORA. Sayyadi Tooranloo and Ayatollah [29] used interval-valued intuitionistic fuzzy numbers for representing sentiment patterns to evaluate the quality of online banking based on customer sentiments. Liang et al. [23] converted the tourist sentiment preferences derived from the customer reviews into a distributed linguistic form and proposed a distributed linguistic-VIKOR approach for the evaluation and ranking of hotels. Serrano-Guerrero et al. [33] used type-1 FSs for representing customer sentiments about hotels and aggregated the sentiments using type-1 OWA operators to derive the polarity. Some studies have been conducted specifically in the area of recommender systems based on opinion sentiment analyses. For instance, the notation of doctors' performance based on patient opinions has been analyzed through the use of opinion sentiment analysis. This was carried out differently in the studies conducted by Li et al. [24], where the authors used opinion sentiment analysis to develop probabilistic linguistic term sets to assess doctors' performance. This was based on patient opinions obtained from the hospital. In other studies carried out by Chen and Li [7] and Serrano-Guerrero et al. [1], the authors used the doctors' performance as the basis for their studies. Patient opinions were determined in both studies through the use of probabilistic linguistic term sets. In another case, the authors Serrano-Guerrero et al. [32] used IVPFs. Abirami and Askarunisa [1] employed a linguistic method to identify opinion-carrying terms from hospital reviews and employed the usage of opinion.StylePriority Although only a few studies are based on Pythagorean fuzzy sets (PFSs), the majority of the previous studies related to sentiment analysis were performed utilizing different forms of fuzzy systems. For example, He et al. [16] employed PFSs for the representation of opinion positivity, negativity, and neutrality and included the role of regret-based psychological behavior. Quek et al. [27] used PFSs for the construction of opinion decision-making fusion for stock market trading and proved the effectiveness of opinion modeling in improving the future outcome.

2.1 **Entropy Weight Method**

A commonly used objective technique for estimating the relative weights of assessment criteria in multi-attribute decision-making (MADM) situations is the Entropy Weight Method. Entropy, which is based on information theory, quantifies how chaotic or unpredictable a set of data is. By figuring out each criterion's entropy value, this metric in decision analysis estimates the amount of information each criterion contributes. More fluctuation or uncertainty in the criterion's values will be implied by a higher entropy score, which means that the decision will contain less discriminatory information. Criteria that are more stable and selective will indicate lower entropy values, making them more informative. As a result, the technique gives weights that are inversely proportional to the entropy values, giving greater weights to criteria that are more stable and selective. By limiting human bias and concentrating on the most important aspects, this adds objectivity to the decision-making process.

2.2 **Multi-Attribute Decision-Making (MADM) Methods**

A group of decision-making tools known as Multi-Attribute Decision-Making (MADM) approaches are used to evaluate and rank options based on a number of potentially conflicting attributes. They are particularly helpful when it is difficult to compare options since each one performs differently on multiple attributes. The Analytic Hierarchy Process (AHP), Weighted Sum Model (WSM), and Weighted Product Model (WPM) are a few popular MADM techniques that provide preference ranks by the explicit aggregation of criteria using methodical procedures. In this work, we use a MADM approach to mitigate uncertainty and indeterminacy in expert evaluations by merging picture fuzzy set theory with entropy objective weighting. An informed and fair assessment system that supports sound decision-making is made possible by recommend the best hospital.

3. Methods and Materials

3.1 Dataset

The dataset gathered in [13] will be used to evaluate the effectiveness of this proposal. The collection includes the views of eight hospitals' patients and visitors. These statistics are from Careopinion, one of the most significant websites that aggregates patient reviews of hospitals across the globe. All viewpoints were gathered from UK hospitals and written in English; this plan does not take into account comments in other languages. Because this web platform prohibits users from writing brief opinions, every opinion that is assessed uses at least ten terms.

3.2 Picture fuzzy set

This works on the premise of opinion modeling based on the degree of neutrality, positivity, negativity, and reluctance. The theory of PFS, as related to IFSs and first proposed by Cuong [59], has to be used in order to accomplish the aforementioned. This has the potential to denote additional information like the degree of yes, no, abstains, and refusal for the decision-makers compared to the IFSs because the latter denotes the degree of membership and non-membership.

Definition 3.1 A Picture Fuzzy Set (PFS) on a nonempty set X is defined as $P = \{\langle x, (T_\gamma(x),\, I_\gamma(x),\, F_\gamma(x))\rangle \mid x \in X\}$ where $T_\gamma(x)$, $I_\gamma(x)$, and $F_\gamma(x)$ denote the positive, neutral, and negative membership degrees, respectively, and they satisfy the condition $0 \le T_\gamma(x) + I_\gamma(x) + F_\gamma(x) \le 1$.

Theorem 3.1 *Let $\gamma_i = \big(T_\gamma(x_i),\, I_\gamma(x_i),\, F_\gamma(x_i)\big)$, for $i = 1, 2, 3, \ldots, n$ be a collection of Picture Fuzzy Sets (PFS). Then the Picture Fuzzy Weighted Aggregation (PWAw) operator and the Picture Fuzzy Weighted Geometric (PWGw) operator are defined as follows:*

$$PWAw(\gamma_1, \ldots, \gamma_n) = \left(1 - \prod_{i,j=1}^{n}(1 - T_\gamma(x_i))^{w_j},\ \prod_{i,j=1}^{n}(I_\gamma(x_i))^{w_j},\ \prod_{i,j=1}^{n}(F_\gamma(x_i))^{w_j}\right),$$

$$PWGw(\gamma_1, \ldots, \gamma_n) = \left(\prod_{i,j=1}^{n}(T_\gamma(x_i))^{w_j},\ 1 - \prod_{i,j=1}^{n}(1 - I_\gamma(x_i))^{w_j},\ 1 - \prod_{i,j=1}^{n}(1 - F_\gamma(x_i))^{w_j}\right).$$

where $w = (w_1, w_2, w_3, \ldots, w_n)^T$ is the weight vector of γ_j $(j = 1, 2, \ldots, n)$ such that $w_j > 0, \quad \sum_{j=1}^{n} w_j = 1$.

Definition 3.2 Let $\gamma_i = \{(T(x_i),\, I(x_i),\, F(x_i)) \mid x_i \in X\}$ be a neutrosophic set (NS) on X. Then the entropy of γ_i is defined as $E(\gamma_i) = 1 - \frac{1}{2m}\sum_{i=1}^{m}\Big[\big(T_\gamma^4(x_i) + I_\gamma^4(x_i)\big)\sqrt{\left|256F_\gamma^4(x_i) - 1\right|} + \big(T_\gamma^4(x_i) + F_\gamma^4(x_i)\big)\sqrt{\left|256I_\gamma^4(x_i) - 1\right|} + \big(F_\gamma^4(x_i) + I_\gamma^4(x_i)\big)\sqrt{\left|256T_\gamma^4(x_i) - 1\right|}\Big]$.

Theorem 3.2 *The proposed entropy on $NS(X)$ satisfies the following conditions:*

1. *$E_{\gamma_i} = 0$, if γ_i is a crisp set, i.e., $\gamma_i = (T_\gamma(x_i), I_\gamma(x_i), F_\gamma(x_i)) = (1, 0, 0)$ or $\gamma_i = (0, 0, 1), \forall\, x_i \in X$.*
2. *$E_{\gamma_i} = 1$, if $\gamma_i = \left\{x_i, \left(\frac{1}{4}, \frac{1}{4}, \frac{1}{4}\right) \mid x_i \in X\right\}$.*
3. *$E_{\gamma_i} = E_{\gamma_i^c}$, for all $\gamma_i \in NS(X)$.*
4. *$E_{\gamma_i} \le E_{\delta_i}$ if either $T_\gamma(x_i) \le T_\delta(x_i)$, $I_\gamma(x_i) \le I_\delta(x_i)$, $F_\gamma(x_i) \le F_\delta(x_i)$, when $\max\{T_\delta(x_i),\, I_\delta(x_i),\, F_\delta(x_i)\} \le \frac{1}{2}$, or $T_\gamma(x_i) \ge T_\delta(x_i)$, $I_\gamma(x_i) \ge I_\delta(x_i)$, $F_\gamma(x_i) \ge F_\delta(x_i)$, when $\min\{T_\delta(x_i),\, I_\delta(x_i),\, F_\delta(x_i)\} \ge \frac{1}{2}$.*

Proof.

(1) Let $\gamma_i = \big(T_\gamma(x_i),\, I_\gamma(x_i),\, F_\gamma(x_i)\big) = (1,0,0), \forall\, x_i \in X$. Then $E(\gamma_i) = 1 - \frac{1}{2m}\sum_{i=1}^{m}\Big[(T_\gamma^4(x_i) + I_\gamma^4(x_i))\sqrt{|256F_\gamma^4(x_i)-1|} + (T_\gamma^4(x_i)+F_\gamma^4(x_i))\sqrt{|256I_\gamma^4(x_i)-1|} + (F_\gamma^4(x_i)+I_\gamma^4(x_i))\sqrt{|256T_\gamma^4(x_i)-1|}\Big]$.
Substituting $(T,I,F)=(1,0,0)$: $E(\gamma_i) = 1-\frac{1}{2m}\sum_{i=1}^{m}[(1^4+0)\sqrt{|256\cdot 0-1|}+(1^4+0)\sqrt{|256\cdot 0-1|}$ $+(0+0)\sqrt{|256\cdot 1-1|}]. = 1-\frac{1}{2m}\sum_{i=1}^{m}2 = 1-\frac{1}{2m}(2m) = 1-1 = 0$. Similarly, if $\gamma_i = (0,1,0)$ or $(0,0,1)$, $\forall x_i \in X$, then again $E(\gamma_i)=0$.

(2) Let $\gamma_i = \left\{(x_i, \frac{1}{4}, \frac{1}{4}, \frac{1}{4}) \mid x_i \in X\right\}$. Then $E(\gamma_i) = 1-\frac{1}{2m}\sum_{i=1}^{m}\Big[\big(T_\gamma^4(x_i)+I_\gamma^4(x_i)\big)\sqrt{|256F_\gamma^4(x_i)-1|} + \big(T_\gamma^4(x_i)+F_\gamma^4(x_i)\big)\sqrt{|256I_\gamma^4(x_i)-1|} + \big(F_\gamma^4(x_i)+I_\gamma^4(x_i)\big)\sqrt{|256T_\gamma^4(x_i)-1|}\Big]$
$= 1-\frac{1}{2m}\sum_{i=1}^{m}\Big[\left(\frac{1}{4^4}+\frac{1}{4^4}\right)\sqrt{\left|256\left(\frac{1}{4^4}\right)-1\right|}+\left(\frac{1}{4^4}+\frac{1}{4^4}\right)\sqrt{\left|256\left(\frac{1}{4^4}\right)-1\right|}+\left(\frac{1}{4^4}+\frac{1}{4^4}\right)\sqrt{\left|256\left(\frac{1}{4^4}\right)-1\right|}\Big] = 1 - \frac{1}{2m}\sum_{i=1}^{m}\left[\left(\frac{1}{256}+\frac{1}{256}\right)|1-1|+\left(\frac{1}{256}+\frac{1}{256}\right)|1-1|+\left(\frac{1}{256}+\frac{1}{256}\right)|1-1|\right] = 1-0=1.$

(3) $E(\gamma_i) = 1-\frac{1}{2m}\sum_{i=1}^{m}\Big[(T_\gamma^4+I_\gamma^4)\sqrt{|256F_\gamma^4-1|}+(T_\gamma^4+F_\gamma^4)\sqrt{|256I_\gamma^4-1|}+(F_\gamma^4+I_\gamma^4)\sqrt{|256T_\gamma^4-1|}\Big]$. For the complement $\gamma_i^c = (F_\gamma, I_\gamma, T_\gamma)$, the expression becomes: $E(\gamma_i^c) = 1-\frac{1}{2m}\sum_{i=1}^{m}\Big[(F_\gamma^4+I_\gamma^4)\sqrt{|256T_\gamma^4-1|}+(F_\gamma^4+T_\gamma^4)\sqrt{|256I_\gamma^4-1|}+(T_\gamma^4+I_\gamma^4)\sqrt{|256F_\gamma^4-1|}\Big]$. This is exactly the same expression $E(\gamma_i)=E(\gamma_i^c)$.

(4) Let $T_\gamma(x_i)\le T_\delta(x_i)$, $I_\gamma(x_i)\le I_\delta(x_i)$, $F_\gamma(x_i)\le F_\delta(x_i)$, and $\max\{T_\delta(x_i), I_\delta(x_i), F_\delta(x_i)\}\le\frac{1}{2}$.

Then each term satisfies monotonicity: $(T_\gamma^4+I_\gamma^4)\sqrt{|256F_\gamma^4-1|}\le(T_\delta^4+I_\delta^4)\sqrt{|256F_\delta^4-1|}$ and similarly for the other two terms. Thus, $1-\frac{1}{2m}\sum_{i=1}^{m}E_\gamma(i) \le 1-\frac{1}{2m}\sum_{i=1}^{m}E_\delta(i)$,
which implies: $E(\gamma_i)\le E(\delta_i)$.
This completes the proof.

Definition 3.3 The degree of divergence of the criteria is defined as $d_j^P = 1-E(P)$, which increases as the entropy value decreases.

Definition 3.4 The weight of the criteria is given by $w_j = \dfrac{d_j^P}{\sum\limits_{j=1}^{n} d_j^P}$.

Definition 3.5 Let $(\lambda_a, \mu_a, \pi_a)$ be a picture fuzzy number. Then the score function is defined as $S = \frac{2+\lambda_a-\mu_a-\pi_a}{3}$.

4. Experiments and Results

4.1 **Evaluation Criteria:**

Evaluation Criteria: To guarantee a thorough assessment that satisfies the demands of patients and healthcare stakeholders, a number of variables must be taken into account when choosing the finest healthcare facility. These characteristics, also known as criteria, are the primary decision-making parameters used to assess and rank healthcare facilities in the framework of Multi-Attribute Decision-Making (MADM). MADM techniques make it possible to compare alternative healthcare facilities according to a number of factors, resulting in a well-informed, methodical, and data-driven choice.

Some fundamental and often used criteria for choosing the best hospital facility include the following, though they can change based on the particular medical needs:

1. Clinical effectiveness (CE):

Clinical effectiveness measures how well a hospital delivers treatments and medical interventions that result in desired health outcomes. It focuses on whether the care provided is evidence-based, safe, and successful in improving patients' health conditions.

2. Staff orientation (SO):

Staff orientation refers to how well a hospital prepares, trains, and engages its medical and non-medical staff to provide safe, efficient, and patient-centered care. It reflects the hospital's commitment to building a skilled, motivated, and well-coordinated workforce.

3. Efficiency (E):

Efficiency in a hospital context refers to how well the hospital utilizes its resources such as staff, equipment, time, and finances to deliver high-quality care with minimal waste. It reflects the hospital's ability to achieve the best possible outcomes while optimizing cost, time, and resource usage. **4. Responsive governance (RG):**

Responsive governance in a hospital context refers to the hospital's ability to make timely, transparent, and accountable decisions that prioritize patient welfare and service quality. It reflects how effectively the hospital administration listens to stakeholders (patients, staff, regulators) and acts on their needs or concerns.

5. Safety (S):

Safety in a hospital context refers to how well a hospital protects patients, staff, and visitors from medical errors, infections, and accidents, ensuring a secure environment for treatment and recovery. It is one of the most critical indicators of healthcare quality because it directly impacts patient outcomes and trust.

4.2 **Evaluation Process:**

In Table 1 defined the PF decision matrix and it can be considered as a decision matrix and all the aspects are benefit types.

H	**CE**	**SO**	**E**	**RG**	**S**
H1	$\langle 0.66, 0.13, 0.18 \rangle$	$\langle 0.64, 0.11, 0.25 \rangle$	$\langle 0.56, 0.13, 0.30 \rangle$	$\langle 0.56, 0.09, 0.34 \rangle$	$\langle 0.36, 0.15, 0.47 \rangle$
H2	$\langle 0.62, 0.11, 0.25 \rangle$	$\langle 0.63, 0.11, 0.25 \rangle$	$\langle 0.56, 0.13, 0.30 \rangle$	$\langle 0.50, 0.13, 0.36 \rangle$	$\langle 0.33, 0.10, 0.55 \rangle$
H3	$\langle 0.63, 0.12, 0.24 \rangle$	$\langle 0.60, 0.12, 0.27 \rangle$	$\langle 0.51, 0.14, 0.34 \rangle$	$\langle 0.51, 0.11, 0.37 \rangle$	$\langle 0.33, 0.12, 0.54 \rangle$
H4	$\langle 0.65, 0.10, 0.24 \rangle$	$\langle 0.67, 0.09, 0.22 \rangle$	$\langle 0.52, 0.14, 0.33 \rangle$	$\langle 0.49, 0.13, 0.36 \rangle$	$\langle 0.32, 0.11, 0.55 \rangle$
H5	$\langle 0.61, 0.10 0.28 \rangle$	$\langle 0.60, 0.09, 0.30 \rangle$	$\langle 0.51, 0.14, 0.33 \rangle$	$\langle 0.49, 0.14, 0.36 \rangle$	$\langle 0.34, 0.11, 0.54 \rangle$

Table 1: Picture fuzzy decision matrix for healthcare centres

Using the proposed entropy we will get the entropy, Degree of divergence and weight of the criteria in Table 2.

Methods / Criteria	**CE**	**SO**	**E**	**RG**	**S**
Entropy Value	0.85999076	0.860658	0.874155	0.85831	0.857388
Degree of Divergence D_j^p	0.14000924	0.139342	0.125845	0.14169	0.142612
Weight of the Criteria W_j^p	0.203059430	0.202092	0.182517	0.205497	0.206834

Table 2: Entropy, divergence, and weight values for healthcare decision criteria

H	**T**	**F**	**I**
H1	0.5689	0.1231	0.2980
H2	0.5407	0.1213	0.3337
H3	0.5278	0.1249	0.3428
H4	0.5527	0.1181	0.3274
H5	0.5232	0.1176	0.3561

Table 3: The aggregating results by the PWA_w operators

In Table 3, The aggregating values found by using PWA_w operator

H	**T**	**F**	**I**
H1	0.5458	0.1251	0.3210
H2	0.5160	0.1218	0.3600
H3	0.5047	0.1254	0.3675
H4	0.5188	0.1194	0.3579
H5	0.5039	0.1195	0.3743

Table 4: he aggregating results by the PWG_w operators

In Table 4, The aggregating values found by using PWG_w operator

H	$\mathbf{PWA_w}$	$\mathbf{PWG_w}$
H1	0.7159	0.6999
H2	0.6952	0.6781
H3	0.6867	0.6706
H4	0.7024	0.6805
H5	0.6832	0.6700

Table 5: The score values

In table 5, we find the score values by using aggregating values from table 4.

Operators	**Ranking**
PWAw	H1 > H4 > H2 > H3 > H5
PWGw	H1 > H4 > H2 > H3 > H5

Table 6: Ranking of healthcare centres based on PWA_w and PWG_w operators

Table 6, represented the ordering of Hospital. From this table we conclude H1 is the best Hospital comparing with others.

4.3 **Visualization of Ranks**

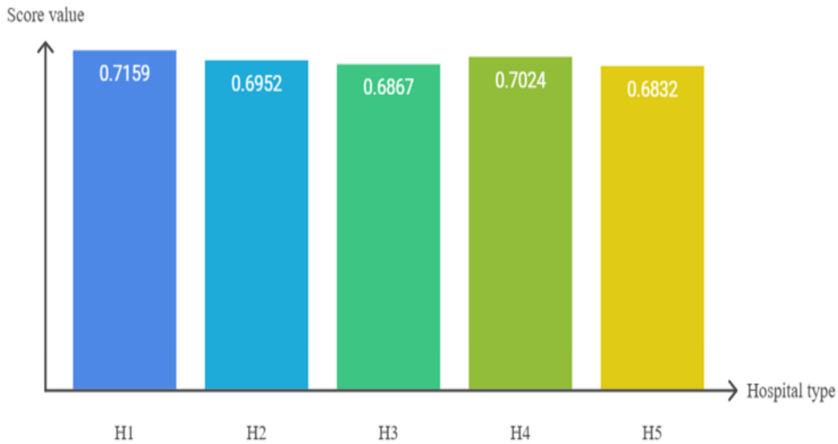

Figure 1: Comparison of H1 to H5 by the score values of PWA_w

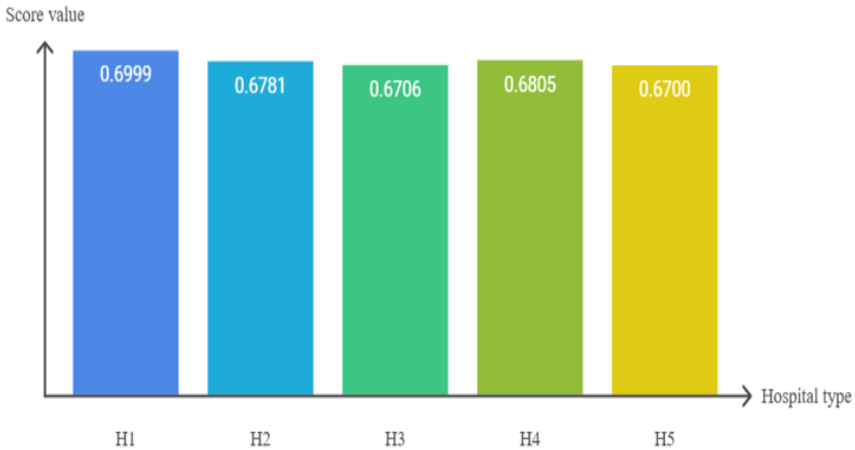

Figure 2: Comparision of H1 to H5 by the score values of PWG_w

5. Conclusions

In this paper a PFE based MADM framework for patient feedback-based tailored hospital recommendations is presented. The model successfully handles subjectivity and uncertainty in decision-making by taking into account positive, neutral, negative reactions. The method offers precise hospital rankings based on a number of factors, allowing for more data-driven and patient-centred recommendations. From score functions we conclude H1 is the best hospital. Real-time feedback integration and validation with bigger datasets might be part of future research.

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