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A Hybrid Best Worst Method and TOPSIS Methodology for Multi-Criteria Hospital Ranking in Neutrosophic Settings

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ABSTRACT: This study presents a hybrid decision-making framework for hospital ranking that combines the Best–Worst Method (BWM), Single-Valued Neutrosophic Sets (SVNS), and the TOPSIS. Unlike previous research that combined BWM with conventional TOPSIS, this study innovatively applies BWM alongside SVN–TOPSIS, a less explored method for ranking hospitals. Data were collected from hospital administrators based on criteria that included service quality, infrastructure, readiness of staff and equipment, payment options, reliability, and affordability. BWM was employed to determine consistent weights for these criteria, SVNS addressed uncertain or incomplete data, and TOPSIS was used to derive the rankings. Sensitivity analysis with weight variations between 5% and 30% demonstrated the robustness of the rankings, validated by a Spearman's rank correlation coefficient of 0.974. The findings confirm that this method is dependable and has potential applications in other uncertain decision-making contexts.

Keywords: Hybrid decision-making framework, Best-Worst method, SVNS, TOPSIS, hospital ranking, MCDM, criterion weighting, uncertainty, expert judgment, healthcare evaluation.

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1. Introduction

Assessing and grading hospital performance is a complex task in the modern healthcare industry. In particular, multispecialty hospitals must be evaluated based on a number of factors, including cost-effectiveness, operational efficacy, patient satisfaction, and clinical quality. Enhancing patient happiness is a strategic goal with numerous advantages as well as an ethical obligation, as discussed in the review paper by Omaghomi et al. [1]. Effective management techniques, such as strong leadership, empathetic and transparent communication, initiatives to improve quality, and the development of an organizational culture focused on the needs of the patient, are crucial to its success.

In an article [2], by Mohapatra et al., it was stated that the process of ranking hospitals is difficult, as it involves managing a lot of underlying data. Typically, the procedure involves evaluating various aspects of service and quality. Clinical care and patient care experiences are two aspects of evaluating the overall quality of hospital care.

The nine-plus-one framework provides an easy-to-use method for evaluating and comparing the performance of health systems, according to a study by Müller et al. [3]. China, India, Brazil, the United States, Russia, Germany, Japan, the United Kingdom, France, Singapore, and Switzerland are among the countries whose health systems use the framework. For every indication, pertinent information was gathered from official websites and/or published reports in peer-reviewed journals. It does not make use of a

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number of MCDM's fundamental advantages, including stakeholder participation, advanced aggregation, sensitivity analysis, adjustable weighting, and explicit uncertainty treatment.

In order to rate hospitals according to the following criteria: hospital registration, payment, outpatient, inpatient, emergency, and pharmacy, Habibi et al. [4], compared three MCDM techniques, including TOPSIS, MOORA, and their combination. Although the study uses MCDM methodologies to rank hospitals, it leaves out important components of MCDM rigor, such as stakeholder participation, transparent weighing, in-depth sensitivity analysis, and uncertainty modeling. These restrictions reduce the rankings' generalizability and resilience for use in actual decision-making.

The article by Kadoić et al. [5] employed a MCDM methodology by combining composite indicators with the Analytic Hierarchy Process. After weighting, the criteria values were normalized and aggregated into composite indicators for each hospital. Hospitals were then ranked, identifying the top 40% best-performing public acute hospitals at the national level. The study performed sensitivity analysis through Monte Carlo simulation, varying weights within a ±15% range. However, it could benefit from broader stakeholder engagement, integration of qualitative factors, consideration of hybrid or alternative MCDM methods, and deeper modeling of uncertainty for an even more robust and comprehensive evaluation.

The study by Singh [6] integrated Fuzzy AHP and ELECTRE-I to rank hospitals by service quality, using Fuzzy AHP for criteria weighting and ELECTRE-I for handling conflicting criteria in final rankings. This hybrid approach offers a comprehensive, reliable decision-making framework for hospital selection. However, subjectivity in expert evaluations and limited validation in diverse settings may affect ranking accuracy and generalizability.

Fuzzy TOPSIS is a MCDM technique that incorporates uncertainty and imprecision in the evaluation process by using fuzzy logic. In the study by Chou et al. [7],the relative closeness to the ideal solution was calculated to rank alternatives effectively in healthcare selection scenarios. One problem with fuzzy TOPSIS is that it needs careful selection of membership functions and linguistic scale parameters. This can make the findings less reliable because the decision makers can configure these fuzzy parameters in different ways.

Ranking healthcare providers involves evaluating multiple, often differing and abstruse criteria such as quality, cost, and patient satisfaction, where data is frequently incomplete, imprecise, or expressed in vague terms. This leads to uncertainty, such as inaccurate or missing measurements, and indeterminacy, such as ambiguous definitions, subjective judgments, and overlapping performance, making traditional ranking methods inadequate. Compared to traditional fuzzy methods, SVN approaches are becoming more popular in research these days, particularly for problems like hospital rating where uncertainty, indeterminacy, and inconsistency all coexist [8].

A reliable multi-criteria decision-making process that makes use of reliable optimization approaches in the face of uncertainty is the BWM. One advantage of the BWM is that it requires fewer paired comparisons, making it a very time- and data-efficient method for establishing criteria weights with higher reliability and consistency. Furthermore, it reduces biases and offers the possibility of more reliable and accurate choice results by pre-identifying the best and worst criteria and employing two vectors of comparisons, making it appropriate for both individual and group decision-making situations [9].

A strong tool for establishing criteria weight coefficients and making decisions based on several criteria is the BWM. Nonetheless, there are certain multi-criteria challenges in real-world problem solving when multiple factors have an equal impact on making a decision. The conventional BWM postulates suggest identifying one best criterion and one worst criterion from among a collection of discovered criteria in such circumstances. The traditional BWM was improved in this study by Pamučar et al. [10] Even when there are multiple best and worst criteria, decision-makers can still express their preferences using the enhanced BWM (BWM-I).

To aid in the selection of smart medical equipment, Abdel-Basset et al. [11] suggested a group decision-making framework utilizing TOPSIS approach. It employed the TOPSIS technique to rank options based on their proximity to ideal solutions and incorporated SVNS sets to address the uncertainty and indeterminacy inherent in expert evaluations. The framework is helpful for group decision-making in complex medical equipment selection situations since it allows combining the perspectives of several experts. Because inputs are subjective, the technique may encounter issues with the consistency and dependability of expert opinions.

Using SVN-numbers, which can represent truth, indeterminacy, and falsity for unknown values, the study suggests a framework for resolving MADM problems. To efficiently compare and rank options under uncertainty, it presents cut set concepts for SVN, SVTN (trapezoidal), and SVTrN (triangular) numbers, specifies their values and ambiguities, and establishes a ranking system based on these metrics [12,13].

The decision-making issue in sports is identified in this work by Anwar et al. [14]. It suggested a neutrosophic TOPSIS method for assessing performance and selecting the series' top bowler and batsman. When dealing with imprecision, indeterminacy, vagueness, and inconsistency in real-world problems, the method is effective, reliable, and well-structured.

The suggested framework offers a solid basis for allocating resources and making strategic plans, making it perfect for complicated contexts with little data. Despite uncertainty, the BWM consistently determines weights for certain hospital evaluation categories using expert opinion. Neutrosophic TOPSIS with SVNS environment effectively manages uncertainty and indeterminacy in hospital performance data, delivering a robust ranking by comparing alternatives to ideal solutions. This approach excels in complex decision-making contexts like hospital ranking, where expert opinions can be subjective, information is incomplete, and criteria are conflicting, thereby enhancing the precision and reliability of assessments under uncertainty.

This article presents Hausdorff distance and similarity measures tailored for SVNS, which provide a more flexible way of handling uncertainty and indeterminacy in data. Using these measures, the authors design a framework for MCDM that improves the accuracy and reliability of evaluating alternatives in complex decision environments. But the computation of Hausdorff distance and similarity measures for SVNs can be complex and resource-intensive when the number of criteria or alternatives is large, which may limit its practical use in very large-scale decision problems [15].

The remaining portion of this paper is structured as follows. Section 2 presents the core methodologies of BWM, SVNSs, and the TOPSIS approach, along with the integration of neural networks within this context. It introduces the proposed Neutrosophic TOPSIS approach based on the SVNS framework for hospital ranking. In Section 3, the methodology is applied to evaluate hospital performance across six criteria, using real data gathered from domain experts such as medical professionals and hospital administrators. Section 4 elaborates on the results and the findings. Concluding remarks are included in Section 5, and lastly acknowledgements and references.

2. Methodology

2.1. Proposed Framework

The framework designed to identify and recommend hospital ranking is illustrated in Figure 1 and involves several key phases.

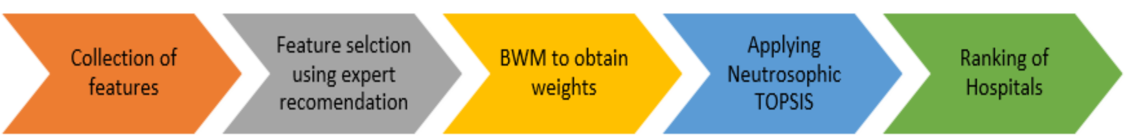

Figure 1: Proposed framework for hospital ranking

Initially, relevant data is gathered from different literature of MCDM, and then important features are selected and extracted from this dataset using a feature selection method [16]. For expert consultation, public and private multispecialty hospitals were considered. Through expert consultation, the best and worst criteria are determined, and the chosen criteria are normalized. Once normalization is complete, the weights of the criteria are calculated. The crisp data is transformed into single-valued neutrosophic numbers (SVN), forming a neutrosophic decision matrix. In the final stage, neutrosophic TOPSIS is employed to analyze this matrix and recommend the best hospital. Each step of the process is discussed in detail below [17]. In typical frameworks combining BWM and Neutrosophic TOPSIS, the following steps were followed.

In the BWM, the decision-maker first identifies the most important and least important criteria. Next, pairwise evaluations are carried out between the best criterion and all other criteria, and between each criterion and the worst one. These comparison results are then used to formulate and solve a maximin optimization problem, which yields the optimal weights for all criteria.

We can utilize a systematic approach based on expert judgment priorities in this study to determine which of the six hospital-related criteria is the most significant and which is the least relevant for use in approaches like BWM.

The following is the graphic flow diagram to understand the framework, Figure 2.

Figure4 to undestand the steps in this process

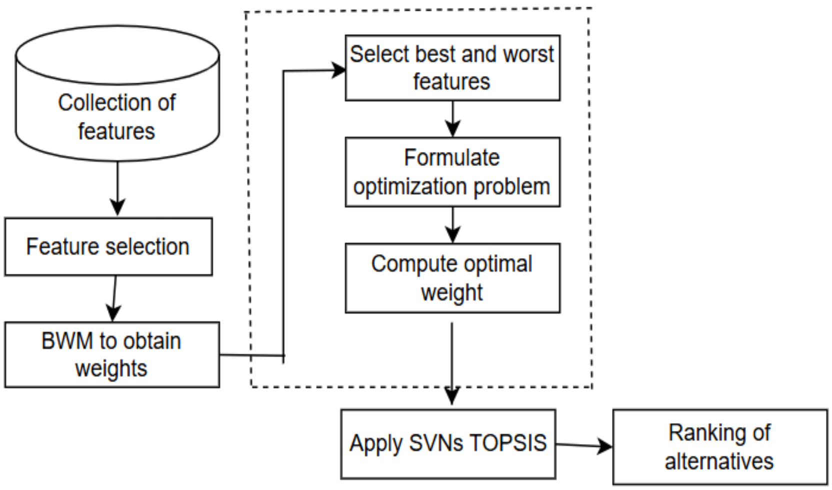

Figure 2: Graphical Flow Chart

2.2. Best-Worst Method

The weights obtained from the BWM represent the relative importance of each criterion, reflecting expert preferences under uncertainty. The Figure 3 explains all the steps required in this process.

Let $C = \{C_1, C_2, \ldots, C_n\}$ be the customary criteria.

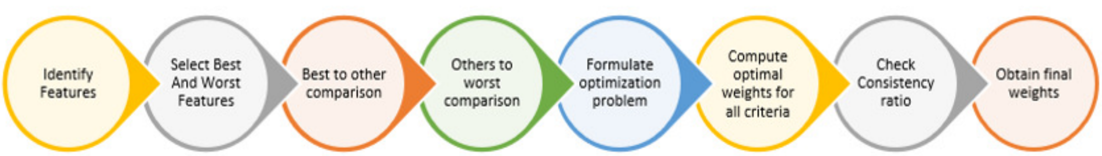

Figure 3: Steps to obtain weights by using BWM

The best criterion C_B and the worst criterion C_W, according to expert judgment, must be identified. The decision-maker or expert assigns a preference score for the criterion C_B compared to the other criteria, using a scale from 1 to 9. A value of 1 indicates equal importance, while a value of 9 indicates that it C_B is extremely more important [18] . The numbers between 1 and 9 represent intermediate levels of importance. Then, there will be a pairwise comparison for Best-to-Others and Worst-to-Others. Experts rate the preference for the best criterion C_B over all others:

$$A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn}) \tag{2.1}$$

where

and higher values indicate a stronger preference. Now, rate the others on the worst vector:

$$A_W = (a_{1W}, a_{2W}, \ldots, a_{nW}) \tag{2.2}$$

where

$$a_{WW} = 1$$

If the comparisons are completely consistent, then for each j:

$$a_{Bj} \cdot a_{jW} = a_{BW}, \quad \forall j \tag{2.3}$$

But in reality, decision-makers are not consistent, so there will be some deviations. To handle inconsistency, the new term ξ has been introduced, which represents the maximum deviation from consistency. Solving the BWM linear programming model, yields the weights $w_1, w_2, \ldots, w_n$, whuch minimize the maximum absolute deviation ξ.

$$\xi = \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \ \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}, \quad \forall j = 1, \ldots, n \tag{2.4}$$

$$\min \ \xi$$

Subject to the constraints:

$$\left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \quad \forall j \tag{2.5}$$

$$\left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, \quad \forall j \tag{2.6}$$

For n criteria, j ranges from 1 to n.

Here, w_j is the weight assigned to the j^{th} criterion. a_{Bj} is the preference of the best criterion over the j^{th} criterion. a_{jW} is the preference of the j^{th} criterion over the worst criterion. Thus, the notation $\forall j$ means that these constraints must hold for each criterion in the considered set. The optimal w_j are used as criteria weights, and the sum total of the weights should be 1.

$$\sum_{j=1}^{n} w_j = 1, \quad w_j \geq 0 \tag{2.7}$$

The consistency ratio (CR) decides the validity of the weights [18].

2.3. SVNS TOPSIS

The weights obtained from BWM are then applied directly to the normalized neutrosophic decision matrix by multiplying each criterion's SVNS evaluation values by its corresponding weight. In the subsequent distance or neutrosophic correlation coefficient computations to the ideal solutions, Positive Ideal Solution and Negative Ideal Solution, these weighted normalized values are used.

This approach is confirmed by several recent neutrosophic BWM-TOPSIS studies, where BWM serves as the weight elicitation technique and the resulting weights are integrated directly into the neutrosophic TOPSIS ranking process to rank alternatives, e.g. healthcare providers under uncertainty [19]. Refer to Figure 4 to undestand the steps involved in this process. In the next step, construct a neutrosophic

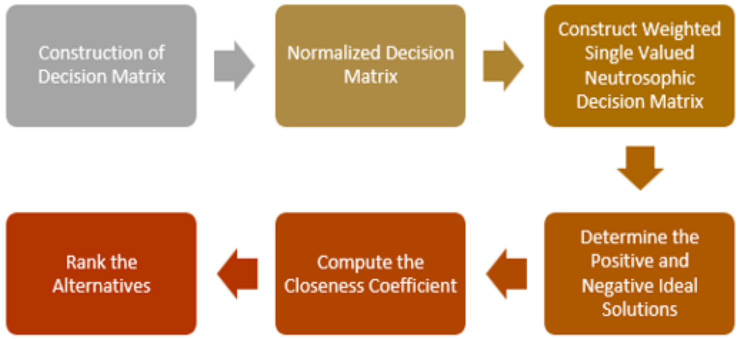

Figure 4: Steps for SVNS TOPSIS for obtaining the ranking of the hospitals

triplet decision matrix for m alternatives (hospitals), each evaluation

$$x_{ij} = (T_{ij}, I_{ij}, F_{ij}) \tag{2.8}$$

where T = truth membership, I = independency, and F = falsity.
The SVNS can be presented in the form of a decision matrix as follows:

$$D = \{(d_{ij})\}_{m\times n} = \begin{bmatrix} d_{11} & \cdots & d_{1n} \\ \vdots & \ddots & \vdots \\ d_{m1} & \cdots & d_{mn} \end{bmatrix} \tag{2.9}$$

In this section, we review key concepts related to single-valued neutrosophic sets (SVNSs) and highlight recent advancements in SVNS-based decision-making methods. Neutrosophic sets introduced by Smarandache (1998) generalize fuzzy sets and intuitionistic fuzzy sets by introducing a truth-membership, indeterminacy-membership, and falsity-membership function [20]. The SVNS proposed by Wang, Smarandache, Zhang, and Sunderraman [21] is a practical subclass of general neutrosophic sets where the membership degrees are restricted to real numbers in [0,1] [22,23].

The truth, indeterminacy, and falsity membership values of the SVNS, a particular kind of neutrosophic set, are restricted to the closed interval instead of the general non-standard interval]0,1[. One of the most often utilized types of neutrosophic sets for decision-making applications, this model is commonly seen in the literature.

One of the definitions of SVNS is as follows: "An SVNS is a neutrosophic set that is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$, and a falsity-membership function $F_A(x)$, where $T_A(x), I_A(x), F_A(x)[0,1]$" [24].

Let U be a universe of discourse. An SVNS A in U is defined as

$$A = \{x, T_A(x), I_A(x), F_A(x) : x \in U\} \tag{2.10}$$

For the given condition,

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3 \tag{2.11}$$

To construct an aggregated weighted single-valued neutrosophic decision matrix, multiply each element of the decision matrix by the weight of the corresponding criterion:

$$d^*_{ij} = w_j \otimes d_{ij} \tag{2.12}$$

The weighted decision matrix is denoted as:

$$D^* = \{(d^*_{ij})\}_{m\times n} \tag{2.13}$$

Determine a normalized decision matrix $\{(N_{ij})\}_{m\times n}$, where

$$N_{ij} = \frac{w_{ij}}{\sum_{j=1}^{m} w_{ij}^2}, \quad i = 1,2,\ldots,n,\ j = 1,2,\ldots,m \tag{2.14}$$

To determine the weighted normalized decision matrix:

$$V = \{(V_{ij})\}_{m\times n}, \quad V_{ij} = w * N_{ij},\ i = 1,2,\ldots,n,\ j = 1,2,\ldots,m \tag{2.15}$$

To identify the SVN Positive Ideal Solution (SVN-PIS) and Negative Ideal Solution (SVN-NIS), classify criteria into Benefit criteria (G_1) and Cost criteria (G_2):

$$NPIS\ (I^+) = \{v_1^+, v_2^+, \ldots, v_n^+\}, \quad v_j^+ = \max(V_{ij}),\ j = 1,2,\ldots,n \tag{2.16}$$

$$NNIS\ (I^-) = \{v_1^-, v_2^-, \ldots, v_n^-\}, \quad v_j^- = \min(V_{ij}),\ j = 1,2,\ldots,n \tag{2.17}$$

To determine the distance of each alternative from NPIS and NNIS:

$$D_i^+ = \sqrt{\sum_{j=1}^{n} \left(V_{ji} - V_i^+\right)^2}, \quad i = 1,2,\ldots,m \tag{2.18}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n} \left(V_{ji} - V_i^-\right)^2}, \quad i = 1,2,\ldots,m \tag{2.19}$$

The relative closeness coefficient (CC) to the ideal solution for each alternative is denoted as:

$$CC_i = \frac{D_i^-}{D_i^+ + D_i^-}, \quad 0 \le CC_i \le 1 \tag{2.20}$$

A larger value of CC_i, indicates a better alternative. The alternatives are ranked based on the descending order of CC_i.

2.4. Sensitivity Analysis:

Introduce random noise to the weights of the criteria for sensitivity analysis in an SVNS-TOPSIS framework. In SVNS-TOPSIS, sensitivity analysis can be done by introducing small random noise to the criterion weights to account for uncertainty in expert judgments or methods like BWM and AHP. By slightly perturbing the weights within a controlled range, such as $\pm 5\%$, each weight is modified by multiplying with $(1 + \text{noise})$, where noise is a random number from the range $[-\delta, +\delta]$. It can then be observed how the rankings of alternatives change. If rankings shift significantly, the model is sensitive to weight variations, whereas stable rankings indicate that the decision process is robust. Steps to introduce random noise: For each weight w_i,

$$w_i' = w_i \times (1 + r_i) \tag{2.21}$$

where $r_i \sim \text{Uniform}[-\delta, +\delta]$.

The normalized weight is given by:

$$\text{Normalized weight} = \frac{w_i'}{\sum_{j=1}^{6} w_j'} \tag{2.22}$$

The Spearman rank correlation coefficient ρ to compare rankings obtained by two different methods can be mathematically expressed as:

$$\rho = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n\,(n^2 - 1)} \tag{2.23}$$

where

n is the number of ranked items (alternatives), $d_i = R_i - S_i$ is the difference between the ranks assigned by R_i (Ranking by TOPSIS method) and S_i (Ranking by Sensitivity Analysis) for the i^{th} item, $\sum d_i^2$ is the sum of the squared differences of the ranks.

3. Results and Discussion

Below are practical guidelines derived from healthcare service quality literature and decision-making research. A clear understanding of all six criteria, along with their associated sub-criteria, is essential, as outlined in Table 1.

Table 1: **Features selected from different articles**

Reference	HSQD	HCIF	HRPO	HFAR	HSSP	HAPS
[25]	✓	✓	×	×	×	×
[26]	✓	✓	×	✓	✓	×
[27]	✓	×	✓	×	✓	✓
[5]	✓	×	×	✓	✓	×
[28]	×	✓	×	✓	✓	×
[3]	✓	×	✓	✓	✓	×
[19]	✓	×	✓	×	×	✓
[29]	×	✓	×	✓	×	×
Prospective approach	✓	✓	✓	✓	✓	✓

HSQD = Hospital Service Quality Dimensions; HCIF = Hospital Credibility and Infrastructure; HRPO = Hospital Reliability and Patient Outreach; HFAR = Hospital Facility Readiness; HSSP = Hospital Stay Safety Provisions; HAPS = Hospital Affordability and Patient Transition Services.

Consultation with domain experts, including hospital managers, clinicians, and patient advocates, is recommended to ensure the highest accuracy (refer Table2).

Table 2: **Recommended for Best Accuracy**

Criteria	Typical Priority Reasoning	Possible Best/Worst Designation
HSQD (C_1)	Direct quality of care impacts satisfaction and outcomes	Best
HSSP (C_2)	Patient safety is essential to avoid harm	Best / Medium
HCIF (C_3)	Important enabler of quality and trust	Medium
HFAR (C_4)	Supports timely quality care	Medium
HAPS (C_5)	Important for access and continuous care	Medium / Worst
HRPO (C_6)	Influences reputation, possibly less direct impact	Worst

Table 3: **Pairwise Comparisons for 'Best-to-Others' and 'Others-to-Worst'**

Criteria	Best-to-Others	Others-to-Worst
HSQD (C_1)	1	7
HSSP (C_2)	2	6
HCIF (C_3)	3	5
HFAR (C_4)	4	4
HAPS (C_5)	5	3
HRPO (C_6)	7	1

Table 4: **Weights For The Criteria Calculated by Applying Python Code**

Criteria	$\mathbf{w_j}$
HSQD (C_1)	0.2595
HSSP (C_2)	0.2595
HCIF (C_3)	0.1730
HFAR (C_4)	0.1297
HAPS (C_5)	0.1038
HRPO (C_6)	0.0741

The Consistency Ratio (CR) obtained is 0.26.

SVNS TOPSIS

Based on the evaluations of the decision makers expressed through the SVNs, the corresponding decision matrix is formulated. The alternative hospitals are labeled with pseudo names (e.g., *Opt1, Opt2*, etc.) to maintain confidentiality.

Table 5: **Decision Matrix Formulated From The Decision Maker's Evaluations Expressed Through SVNs**

D	C_1	C_2	C_3	C_4	C_5	C_6
Opt1	(0.5, 0.2, 0.4)	(0.4, 0.4, 0.4)	(0.9, 0.1, 0.4)	(1.0, 0.6, 0.5)	(0.1, 0.9, 0.3)	(0.4, 0.2, 0.8)
Opt2	(0.6, 0.1, 0.3)	(0.5, 0.7, 0.3)	(0.5, 0.7, 0.5)	(0.8, 0.9, 0.9)	(0.8, 0.3, 0.3)	(0.6, 0.3, 0.1)
Opt3	(0.8, 0.4, 0.3)	(0.8, 0.3, 0.9)	(1.0, 0.3, 0.8)	(0.7, 0.4, 0.9)	(0.5, 0.6, 0.2)	(0.1, 0.1, 0.1)
Opt4	(0.1, 0.8, 0.8)	(0.1, 0.5, 0.2)	(0.1, 0.9, 0.6)	(0.8, 0.5, 0.7)	(0.1, 0.3, 0.8)	(0.6, 0.4, 0.8)
Opt5	(0.5, 0.3, 0.5)	(0.5, 0.8, 0.1)	(0.1, 0.8, 0.8)	(0.7, 0.4, 0.5)	(0.8, 1.0, 0.2)	(0.1, 0.7, 0.5)
Opt6	(0.5, 0.8, 0.5)	(0.5, 0.6, 0.2)	(0.5, 0.2, 0.3)	(0.7, 0.8, 0.9)	(0.8, 0.5, 0.7)	(0.2, 0.5, 1.0)
Opt7	(0.5, 0.6, 0.9)	(0.5, 0.7, 0.4)	(0.3, 1.0, 0.4)	(0.8, 0.5, 0.9)	(0.9, 0.4, 0.0)	(0.0, 0.6, 0.2)
OPt8	(0.8, 0.6, 0.8)	(0.9, 0.8, 0.2)	(0.1, 1.0, 0.9)	(0.9, 0.3, 0.3)	(1.0, 0.9, 0.4)	(0.6, 0.5, 0.1)
Opt9	(0.7, 0.8, 0.6)	(0.6, 0.7, 0.5)	(0.3, 0.3, 0.6)	(0.5, 0.3, 0.1)	(0.6, 0.9, 0.6)	(1.0, 0.9, 0.4)
Opt10	(0.4, 0.2, 0.6)	(0.3, 0.5, 0.2)	(0.2, 0.6, 0.4)	(0.8, 0.2, 0.3)	(0.9, 0.3, 0.9)	(0.3, 0.7, 0.9)

Table 6: **Score Matrix** D^*

D	C_1	C_2	C_3	C_4	C_5	C_6
Opt1	0.4870	0.4480	0.5346	0.4935	0.4429	0.4778
Opt2	0.5260	0.4351	0.4394	0.4352	0.5104	0.5074
Opt3	0.5130	0.4480	0.4913	0.4611	0.4844	0.4963
Opt4	0.3052	0.4221	0.3789	0.4741	0.4481	0.4778
Opt5	0.4610	0.4480	0.3702	0.4870	0.4792	0.4592
Opt6	0.3961	0.4610	0.5000	0.4352	0.4792	0.4518
Opt7	0.3701	0.4221	0.4048	0.4611	0.5260	0.4704
Opt8	0.4221	0.4870	0.3443	0.5195	0.4844	0.5000
Opt9	0.4091	0.4221	0.4481	0.5065	0.4533	0.4889
Opt10	0.4480	0.4480	0.4308	0.5195	0.4844	0.4518

Table 7: **Normalized Score Matrix**

D	C_1	C_2	C_3	C_4	C_5	C_6
Opt1	0.3512	0.3187	0.3858	0.3250	0.2919	0.3158
Opt2	0.3793	0.3095	0.3171	0.2866	0.3363	0.3353
Opt3	0.3700	0.3187	0.3546	0.3037	0.3192	0.3280
Opt4	0.2201	0.3003	0.2735	0.3122	0.2953	0.3158
Opt5	0.3325	0.3187	0.2672	0.3207	0.3158	0.3035
Opt6	0.2857	0.3279	0.3609	0.2866	0.3158	0.2986
Opt7	0.2669	0.3003	0.2922	0.3037	0.3466	0.3109
Opt8	0.3044	0.3464	0.2485	0.3421	0.3192	0.3304
Opt9	0.2950	0.3003	0.3234	0.3336	0.2987	0.3231
Opt10	0.3231	0.3187	0.3109	0.3421	0.3192	0.2986

Table 8: **Weighted Normalized Decision Matrix** V

D	C_1	C_2	C_3	C_4	C_5	C_6
Opt1	0.0912	0.0828	0.0668	0.0422	0.0303	0.0234
Opt2	0.0986	0.0804	0.0549	0.0372	0.0349	0.0248
Opt3	0.0961	0.0828	0.0614	0.0394	0.0331	0.0243
Opt4	0.0572	0.0780	0.0473	0.0405	0.0307	0.0234
Opt5	0.0864	0.0828	0.0462	0.0416	0.0328	0.0225
Opt6	0.0742	0.0852	0.0624	0.0372	0.0328	0.0221
Opt7	0.0693	0.0780	0.0506	0.0394	0.0360	0.0230
Opt8	0.0791	0.0900	0.0430	0.0444	0.0331	0.0245
Opt9	0.0766	0.0780	0.0560	0.0433	0.0310	0.0239
Opt10	0.0839	0.0828	0.0538	0.0444	0.0331	0.0221

In this study, HSQD, HSSP, HCIF, HFAR, and HAPS are considered as Benefit criteria and HRPO as a Cost criterion. The following Table 9 represents the NPIS and NNIS for SVNSs.

Table 9: **Neutrosophic Positive Ideal Solution (I^+) and Negative Ideal Solution (I^-)**

	C_1	C_2	C_3	C_4	C_5	C_6
NPIS (I^+)	0.0986	0.0900	0.0668	0.0444	0.0360	0.0248
NNIS (I^-)	0.0572	0.0780	0.0430	0.0372	0.0303	0.0221

Table 10: **Distances and Performance Scores and Ranking the Alternatives (based on score)**

Alternatives	D_i^+	D_i^-	CC_i	**Rank**
Opt1	0.0120	0.0421	0.7779	2
Opt2	0.0169	0.0434	0.7197	3
Opt3	0.0110	0.0435	0.7986	1
Opt4	0.0477	0.0056	0.1051	10
Opt5	0.0254	0.0302	0.5430	5
Opt6	0.0265	0.0269	0.5039	6
Opt7	0.0359	0.0156	0.3028	9
Opt8	0.0309	0.0262	0.4597	8
Opt9	0.0277	0.0242	0.4668	7
Opt10	0.0212	0.0303	0.5881	4

Opt3 is clearly the best-performing alternative, as it is very close to NPIS and far from NNIS, which shows excellent balance with a score of 0.79. Opt1 and opt2 form the second tier of good options with scores between 0.77 and 0.71, indicating moderate performance. Opt5, Opt6, and Opt10 are acceptable scores of 0.58, 0.54, and 0.50, respectively. Opt7, Opt8, and Opt9 show weaker performance relative to others, with scores of 0.46, 0.45, and 0.30. Particularly, Opt4 is the least preferred option with a score of 0.10.

To introduce random noise (perturbations) within a predefined range to the given weights vector helps to improve robustness and stability [30]. This method ensures realistic variations in weights that simulate uncertainty or subjective bias while keeping the total weight constant. It is commonly used in the sensitivity analysis of Neutrosophic TOPSIS and related multi-criteria decision-making methods.

The perturbation magnitudes for benefit and cost criteria were initially explored, starting from ±5% to evaluate system sensitivity. It was subsequently observed that perturbations of ±30% applied to benefit criteria and ±15% to cost criteria induced moderate ranking fluctuations compared to the original ordering, indicating a degree of ranking sensitivity to these noise levels. This analysis suggests a level of robustness in the ranking outcomes, where stability is maintained under moderate perturbations but exhibits controlled variation beyond certain thresholds. The following Table 11 for the Perturbed weights.

Table 11: **Steps to Introduce Random Noise**

Original weights	**Noise added**	**Perturbed weights**
0.2598	-0.24728615	0.20979878
0.2598	0.00185491	0.27924016
0.17305	-0.14399592	0.15905877
0.1297	-0.02684299	0.13556843
0.1038	0.25448788	0.13986193
0.0741	-0.03916645	0.07647193

The sum of Perturbed weights obtained 1.0. With the perturbed weights, we have calculated Neutrosophic Positive Ideal Solution (I+) and Negative Ideal Solution (I-), and the performance scores with ranks for the alternatives in the Table12.

Table 12: **NPSI (+) and NNSI (-) For Perturbed Weights**

	C_1	C_2	C_3	C_4	C_5	C_6
NPIS (I+)	0.0796	0.0967	0.0614	0.0464	0.0485	0.0227
NNIS (I-)	0.0462	0.0838	0.0395	0.0389	0.0408	0.0255

Table 13: **Distances and Performance Ratings Following the Addition of Noise**

Alternatives	D_i^+	D_i^-	CC_i	**Rank**
Opt1	0.0127	0.0359	0.739	2
Opt2	0.0169	0.0359	0.680	3
Opt3	0.0114	0.0364	0.761	1
Opt4	0.0409	0.0055	0.118	10
Opt5	0.0234	0.0250	0.517	5
Opt6	0.0226	0.0241	0.516	6
Opt7	0.0312	0.0145	0.317	9
Opt8	0.0272	0.0236	0.465	7
Opt9	0.0250	0.0208	0.455	8
Opt10	0.0191	0.0258	0.575	4

This shows that up to 30% noise for benefit criteria and 15% noise for cost criteria are permissible. The bar chart presented in Fig. 4 is a comparison of hospital rankings scores generated by sensitivity analysis and neutrosophic TOPSIS for ten alternatives, Opt1 to Opt10. The ranks assigned by both methods are largely consistent, as shown by adjacent bars of similar heights for each hospital. Hospital Opt3 consistently receives the highest rankings, i.e., the lowest rank numbers, indicating a favourable evaluation. Some variations are observed, such as for Opt6 and Opt8, where rankings differ slightly between the two methods, reflecting sensitivity in their placement.

The comparison includes the Spearman rank correlation coefficient, which is about 0.974, indicating very high similarity between the two rankings. Overall, this comparison suggests that the neutrosophic TOPSIS results align closely with the robustness checks of the sensitivity analysis, supporting confidence in the stability of the ranking (Refer to Figure5).

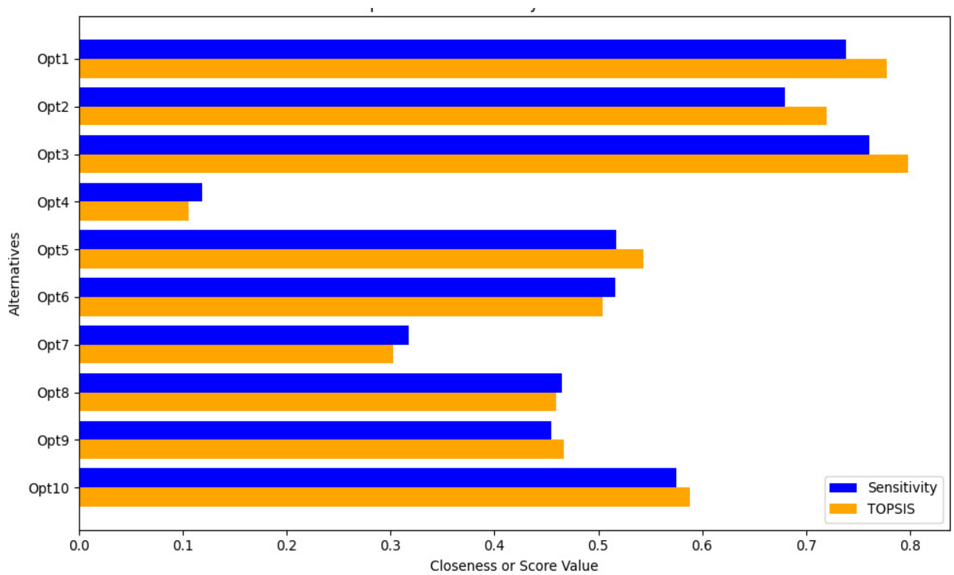

Figure 5: Comparison of ranks from sensitivity and neutrosophic TOPSIS scores for each alternative

This hybrid methodology provides a transparent, robust, and mathematically rigorous tool for healthcare decision-making, accommodating uncertainty and indeterminacy more effectively than conventional methods. The calculated CR value is 0.23. The consistency ratio is a useful tool for investigators to evaluate the appropriateness of the calculated weight. If the CR value is closer to zero, the weights are considered to be more accurate. In the construction of a decision matrix, each alternative is evaluated against each criterion using single-valued neutrosophic numbers, such as membership, indeterminacy, and non-membership values. To conclude, the Neutrosophic TOPSIS evaluation indicates that Opt3 is the most suitable/optimal alternative, while Opt4 is the least suitable. The decision-maker should select Opt3 if the goal is to maximize closeness to ideal performance across all criteria. The results of the neutrosophic with the TOPSIS model are analyzed, showing that the competence of the acquired results and the rankings are sufficiently stable by applying sensitivity analysis.

4. Conclusion

This study proposed a framework that uses the BWM to calculate weights for the criteria, which we obtained from a literature review. This follows the Neutrosophic TOPSIS approach to automate the process of hospital ranking. Data was collected from hospital professionals in linguistic form and converted to numerical values using a scale from 1 to 9. Then the crisp data was converted to a decision matrix with alternatives evaluated under SVNS, including the membership (truth), indeterminacy, and non-membership (falsity) values for each criterion and alternative. Then normalize the decision matrix and calculate weighted values. Determine neutrosophic positive and negative ideal solutions and finally calculate closeness coefficients and rank alternatives. The rankings reflect the relative performance of these alternatives based on the weighted criteria and neutrosophic evaluations. We have employed a sensitivity test by incorporating noise in the weights calculated for each criterion, which demonstrates the robustness of BWM-derived weights and neutrosophic handling of uncertainty in dynamic conditions.

Given the processes involved, the hybrid BWM-SVN TOPSIS method's execution time of 0.006284 seconds shows a very good time efficiency. Such a short runtime on a decision matrix demonstrates that the technique is computationally feasible and practicable for real-world hospital selection situations, since theoretically the order is linear with the product of the number of alternatives and criteria $O(m \times n)$. This framework is applicable in finance, supply chain, healthcare, renewable energy, and numerous other sectors.

The findings presented in the study may provide a basis for further research on related subjects. Nevertheless, the research is predicated on a small sample of survey participants. Internal hospital management procedures, specific facility resources, staffing numbers, and bed capacity are just a few of the variables that are not taken into consideration. Additionally, the framework is used with approximate or aggregated data at the hospital level. These restrictions, such as the small number of medical institutions and the narrow geographic focus, point to areas that could use more investigation to improve the framework's wider application. Innovative methods for hospital ranking have recently been presented through the integration of MCDM with Machine Learning (ML). This new approach combines the advantages of both approaches to provide assessments that are more precise, data-driven, and flexible. These assessments may be included to hospital rating models in the future to improve decision assistance.

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