Neutrosophic Optimization and Intelligent systems

Journal Homepage: sciencesforce.com/nois



Neutrosophic Opt. Int. Syst. Vol. 1 (2024) 57-66

Paper Type: Original Article

Neutrosophic Evaluation of Health Promotion Programs for Resource Allocation

Iván Pimienta Concepción ^{1,*}, Karen Aracelly Tobar Almendariz ¹, and Walter Vayas Valdiviezo ¹

¹ Universidad Regional Autónoma de Los Andes Ambato, Ecuador. Emails: ua.ivanpimienta@uniandes.edu.ec; ua.karentobar@uniandes.edu.ec; ua.waltervayas@uniandes.edu.ec.

 Received: 30 Aug 2023
 Revised: 20 Dec 2023
 Accepted: 20 Jan 2024
 Published: 28 Jan 2024

Abstract

The efficient allocation of resources to health promotion and disease prevention programs in the field of healthcare is a multidimensional and highly sensitive challenge that requires the simultaneous consideration of multiple criteria and objectives. In this context, neutrosophic logic emerges as a promising tool capable of addressing the inherent uncertainty and imprecision in health decision-making. This article explores the application of neutrosophic logic in decision-making regarding the allocation of resources to health promotion and disease prevention programs, taking into account a wide range of criteria. The main objective of this research is to validate the importance of using neutrosophic logic in resource allocation for these programs, emphasizing its ability to handle ambiguity and uncertainty effectively and equitably. The results obtained have demonstrated that neutrosophic logic is an effective tool in decision-making in the field of public health.

Keywords: Prevention Programs, Health, Neutrosophy, TODIM, Resource Allocation.

1 | Introduction

The allocation of resources dedicated to health promotion and disease prevention programs constitutes a critical component of healthcare administration. These programs play an essential role in promoting population health and reducing the burden of diseases in society. However, the task of allotting the necessary resources to these programs is not straightforward, as it involves considering multiple objectives and managing resources that are limited in availability.

To contextualize this challenge, it is relevant to emphasize the significance of health promotion and disease prevention in contemporary society. The burden of chronic diseases and the demand for healthcare services continue to rise, underscoring the need for efficient resource allocation to programs that contribute to reducing disease incidence and improving the quality of life for the population. Furthermore, healthcare systems face constant pressure to optimize available resources to ensure that the community's needs are adequately addressed and public health goals are met.

In reality, the vast majority of dilemmas associated with decision-making involve multiple structures and multiple characteristics, endowing them with a high degree of complexity. The way alternatives are ordered

Corresponding Author: ua.ivanpimienta@uniandes.edu.ec https://doi.org/10.61356/j.nois.2024.17689

Licensee Neutrosophic Optimization and Intelligent systems. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0).

and selected in specific circumstances proves to be the key to resolving such issues [1]. In conventional multicriteria decision-making methods (MCDM), alternatives are commonly evaluated through precise values as a whole. However, due to the intricacy of the environment and the inherent subjectivity of the individuals involved, issues related to multicriteria decision-making often feature the presence of uncertainty [2]. Therefore, the information provided for decision-making is typically vague or of a linguistic nature [3].

The complexity in these cases is intensified by the recurrent presence of uncertainty and imprecision in the healthcare environment, stemming from the inherent variability in health outcomes and the financial constraints that impose budgetary limits [4]. In an ideal scenario, decisions would be based on absolutely precise and comprehensive data, but in reality, data often exhibit shortcomings, ambiguities, and even inaccuracies [5]. Decision-making in practical contexts is characterized by undeniable complexity, arising from the indeterminacies and imprecisions that frequently accompany the available information. This inherent uncertainty can pose challenges to the accurate assessment of situations and the ability to anticipate outcomes [6].

In this context, the 1960s marked significant progress in the search for solutions aimed at addressing the uncertainties present in data in the field of artificial intelligence and decision-making. During this period, mathematician Lotfi A. Zadeh developed the theory of fuzzy logic, which is based on the principle that in many real-world situations, concepts and variables cannot be defined absolutely, that is, as true or false, or by precise numerical values. On the other hand, these concepts and variables have different degrees of membership [7]. However, it is important to note that while fuzzy logic focuses on the representation of fuzzy degrees of membership, it lacks an adequate mechanism to deal with deep ambiguity and uncertainties in contexts where information is presented in incomplete or conflicting ways [8].

A few years later, in the 1990s, the mathematician and philosopher Florentin Smarandache introduced neutrosophic logic as an innovative proposal. Neutrosophic logic was conceived to overcome the limitations of fuzzy logic, particularly when facing situations where not only uncertainty prevails but also the presence of paradoxes, neutral information, and sometimes contradictory information in the da-ta [9].

This logic incorporates three fundamental elements: true, false, and neutral, enabling the representation of uncertainty beyond what is merely fuzzy. That is, it is applied in situations where information is presented in an incomplete or contradictory manner [10]. Neutrosophic logic provides a more comprehensive approach to addressing ambiguity and indeterminations in data and has found applications in various fields, including artificial intelligence, decision-making, and risk management in complex and multifaceted environments [11].

The applications of neutrosophic logic in complex decision-making have expanded into various sectors of the industry [12], the business domain [13], and the sciences [14], thanks to its ability to address situations where uncertainty, ambiguity, and contradictory information pose challenges that test traditional methodologies. Its potential lies in its ability to model and analyze deep uncertainty, allowing professionals to make more informed and adaptable decisions in complex and multifaceted contexts. Neutrosophic logic constitutes a significant expansion of the tools available for decision-making and has the capacity to confront challenges that go beyond the limits of conventional fuzzy logic [15].

In the field of resource allocation to health promotion and disease prevention programs, neutrosophic logic emerges as a promising and essential strategy. The uniqueness of neutrosophic logic lies in its ability to explicitly address uncertainty and imprecision, providing a framework that allows the reflection of degrees of truth, falsity, and indeterminacy. This methodology offers the potential to empower planners with the ability to consider multiple objectives and criteria, including efficiency in resource utilization, equity in access to services, quality of care, and financial sustainability.

In this regard, the main objective of research in this field is to validate the importance and effectiveness of neutrosophic logic in decision-making regarding the allocation of resources to health promotion and disease prevention programs. The aim is to demonstrate that this methodology not only enables dealing with the inherent ambiguity and uncertainty in healthcare management but also leads to a more equitable and efficient

allocation of resources. Neutrosophic logic has the potential to substantially improve the quality of healthcare and contribute significantly to achieving public health goals [16].

To achieve this, this article presents the method proposed by [17], based on the TODIM and PRO-METHEE methods, using Single-Valued Neutrosophic Sets (SVNS). In this work, the neutrosophic theory and the selected method are introduced first. Subsequently, their application is carried out, and finally, the results obtained and the conclusions derived from the study are presented.

2 | Preliminaries

The introduction of Single-Valued Neutrosophic Sets (SVNS) has become a significant approach in set theory and logic to represent ambiguity and uncertainty more precisely. These SVNSs allow describing the membership to truth, indeterminacy, and falseness of an element in a set in a more detailed way, thus finding applications in a wide range of disciplines such as decision-making in uncertain environments, artificial intelligence, and information management.

Let X be a space of points (objects) with generic elements in X represented by x. A Single-Valued Neutrosophic Set A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacymembership function $I_A(x)$, and a falseness-membership function $F_A(x)$. Therefore, an SVNS A can be represented as $A = \{x, T_{A(x)}, I_{A(x)}, F_{A(x)x} \in X\}$, where $T_{A(x)}, I_{A(x)}, F_{A(x)} \in [0, 1]$ for each point x in X. Thus, the sum of $T_{A(x)}, I_{A(x)}$, and $F_{A(x)}$ satisfies the condition $0 \leq T_{A(x)} + I_{A(x)} + F_{A(x)} \leq 3$ [18, 21-22].

Representing these membership functions using values in the range [0, 1] provides greater flexibility and precision in modeling and analyzing situations where uncertainty plays a fundamental role. The range of values [0, 1] ensures that the sum of the membership functions does not exceed 3, which is essential to maintain consistency in the framework of SVNS. This formalization of SVNS in terms of membership functions provides a robust framework for dealing with uncertainty and ambiguity in diverse contexts.

Decision-making typically involves the use of human language, commonly referred to as linguistic variables. A linguistic variable simply represents words or terms used in human language. The use of linguistic variables in decision-making is based on the idea that people often express their preferences and evaluations in a natural and familiar language. This facilitates communication and understanding of criteria evaluations among decision-makers and allows for a representation closer to how people perceive the importance of criteria in a given context.

Therefore, this approach of linguistic variables proves to be a convenient way for decision-makers to express their evaluations. Criteria ratings can be expressed using linguistic variables such as "Very Important" (VI), "Important" (I), "Little Important" (LI), "Not Important" (NI), etc. Linguistic variables can be transformed into single-valued neutrosophic sets (SVNS), as shown in Table 1. The conversion of these linguistic variables into SVNS provides an effective tool for modeling and analyzing uncertainty and ambiguity in decisionmaking, which can be especially relevant in situations where information is imprecise or incomplete.

Integer	Linguistic variable	SVNNs		
0	Not important	(0.90;0.10;0.10)		
1	Low important	(0.75;0.25;0.20)		
2	Medium important	(0.50;0.50;0.50)		
3	High important	(0.35;0.75;0.80)		
4	Very high important	(0.10;0.90;0.90)		

Table 1. Linguistic variable and Single-Valued Neutrosophic Numbers (SVNNs) [19].

According to [19], if $E_k = (T_k, I_k, F_k)$ is a neutrosophic number defined for the rating of the *k*-th decision-maker, then the weight of the *k*-th decision-maker can be expressed as:

$$\psi_k = \frac{1 - \sqrt{\left[(1 - T_k(x))^2 + (I_k(x))^2 + (F(x))^2\right]/3}}{\sum_{k=1}^p \sqrt{\left[(1 - T_k(x))^2 + (I_k(x))^2 + (F(x))^2\right]/3}}$$
(1)

Group decision-making allows for the consideration of diverse perspectives and assessments from multiple decision-makers, enriching the decision-making process and leading to more robust and equitable solutions. In the group decision-making process, all evaluations from individual decision-makers must be aggregated into an aggregated neutrosophic decision matrix. This can be achieved using the Single-Valued Neutrosophic Weighted Average (SVNWA) aggregation operator proposed by [20].

The use of the SVNWA operator facilitates the combination of individual neutrosophic evaluations into a single matrix that represents the group decision more comprehensively and accurately. This approach is particularly valuable in situations where consensus needs to be reached or collective decisions made in complex and multifaceted contexts.

The evaluations of all decision-makers can be compiled into a single decision matrix that reflects the consensus or weighting of individual evaluations based on the assigned weights to each decision-maker. In such a case, given $D_k = (d_{ij}(k))_{mxn}$ as the single-valued neutrosophic decision matrix of the k-th decision-maker and $\psi = (\psi_1, \psi_2, ..., \psi_p)^T$ the vector of decision-maker weights, where each $\psi_k \in [0,1]$, the weighted decision matrix can be obtained by considering [20]:

$$d_{ij} = \langle 1 - \prod_{k=1}^{p} \left(1 - T_{ij}^{(p)} \right)^{\psi_k}, \prod_{k=1}^{p} \left(I_{ij}^{(p)} \right)^{\psi_k}, \prod_{k=1}^{p} \left(F_{ij}^{(p)} \right)^{\psi_k} \rangle$$
(2)

On the other hand, if A and B are assumed to be two single-valued neutrosophic numbers, the normalized Hamming distance between them is defined as:

$$d(A,B)\frac{|TA-TB|+|IA-IB|+|FA-FB|}{3}$$
(3)

The normalized Hamming distance between two single-valued neutrosophic numbers, A and B, measures the discrepancy or difference between them based on their truth, falseness, and indeterminacy components. It is an important indicator to assess how similar or different two SVNNs are in terms of their neutrosophic features. The smaller the normalized Hamming distance, the higher the similarity between A and B, and vice versa. Additionally, the complement of an SVNN $A = (T_A, I_A, F_A)$ can be defined as:

$$A^{C} = (F_{A}, 1 - I_{A}, T_{A})$$
(4)

3 | Methodology

The next procedure supports the TODIM-PROMETHEE method. In this approach, both the values of attributes and their uncertainties are taken into account to evaluate alternatives based on their merits and drawbacks in the decision-making process. This method is particularly valuable in situations with multiple alternatives and attributes, aiming for an objective and equitable evaluation in decision-making based on a neutrosophic number structure.

Let $A = (A_1, ..., A_m)$ be the alternatives and $G = (G_1, G_2, ..., G_n)$ the attributes, the weights to the attributes as $W = (w_1, w_2, ..., w_n)$, where $0 \le w_j \le 1$ and the sum of all the weights is equal to 1, that is, $\sum_{j=1}^{n} w_j = 1$. Let a_{ij} , where i = 1, 2, ..., m and j = 1, 2, ..., n, be the attribute value G_j for the alternative Ai. An m×n dimensional matrix $A = (a_{ij})$ can be created, which is a matrix of single-valued neutrosophic numbers, represented as $\langle (T_{ij}, I_{ij}, F_{ij}) \rangle_{mxn}$, where $T_{ij}, I_{ij}y F_{ij}$ are the degrees of membership, degrees of indeterminacy, and degrees of non-membership, respectively.

The process consists of several key steps:

Step 1. Identify the treatment techniques to be evaluated in the problem.

Step 2. Determine the weights of decision-makers. Each decision-maker is assigned a weight reflecting their experience and knowledge of the problem. These weights are linguistic variables and are represented as SVNN, later identified using a specific equation.

Step 3. Convert linguistic evaluations provided by experts into SVNN. From the crisp integer matrices obtained from expert evaluations, individual neutrosophic matrices are constructed for each decision-maker, following the procedure described in Table 1.

Step 4. Obtain the initial matrix of relationships between alternatives $A = (A_1, ..., A_m)$ and attributes $G = (G_1, G_2, ..., G_n)$. In this matrix, each element a_{ij} represents the value of the attribute G_j for alternative A_i . This matrix is represented as $A = (a_{ij})_{mxn}$ and is expressed as $\langle (T_{ij}, I_{ij}, F_{ij}) \rangle_{mxn}$, where T_{ij} , I_{ij} and F_{ij} are the degrees of membership, degrees of indeterminacy, and degrees of non-membership, determined by a specific equation.

Step 5. Standardize decision information. This involves normalizing matrix $A = (a_{ij})_{mxn}$ to obtain a matrix $B = (b_{ij})_{mxn}$. If the decision is related to a cost factor, decision information is transformed using its complementary set, as indicated in Eq. (3). In the case of an efficiency factor, this change is not required.

Step 6. Build a preference function for the alternative B_i in relation to B_r under the attribute G_j , following the procedure described in Eq. (5).

$$P_{j}(B_{i}, B_{r}) = \begin{cases} 0, d \le p \\ \frac{d-p}{q-p} , p < d < q \\ 1, d \ge q \end{cases}$$
(5)

Step 7. subsequently the relative weight of the attributes w_{jr} is calculated, which is the relative weight G_j to G_r , where

$$w_{jr} = \frac{w_j}{w_r} = (j, r = 1, 2, ..., n)$$
 (6)

Step 8. Define the schema priority $\pi(B_i, B_r)$ index B_i relative to B_r by

$$\pi(B_{i}, B_{r}) = \frac{\sum_{j=1}^{n} w_{jr} P_{j}(B_{i}, B_{r})}{\sum_{j=1}^{n} w_{jr}}$$
(7)

Step 9. Calculate the inflow $\Phi^+(B_i)$, outflow $\Phi^-(B_i)$ and net flow $\Phi(B_i)$ as follows:

$$\Phi^{+}(B_{i}) = \frac{\sum_{r=1}^{m} \pi(B_{i},B_{r}) - \min_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{i},B_{r})\}}{\max_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{i},B_{r})\} - \min_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{i},B_{r})\}}$$
(8)

$$\Phi^{-}(B_{i}) = \frac{\sum_{r=1}^{m} \pi(B_{r},B_{i}) - \min_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{r},B_{i})\}}{\max_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{r},B_{i})\} - \min_{1 \le i \le m} \{\sum_{r=1}^{m} \pi(B_{r},B_{i})\}}$$
(9)

$$\Phi(\mathbf{B}_{i}) = \Phi^{+}(\mathbf{B}_{i}) - \Phi^{-}(\mathbf{B}_{i})$$
⁽¹⁰⁾

Step 10. Rank all alternatives according to the value of Φ (B_i). The higher the value of Φ (B_i), the better the alternative will be. This step involves ranking the alternatives based on their benefits and disadvantages, using the Φ function as the main criterion. The alternatives are ordered from the highest to lowest value of Φ , which makes it easier to identify the best alternative in the context of decision-making.

4 | **Results**

In the context of this study, nine health promotion and disease prevention programs have been identified. These programs require careful prioritization in resource and budget allocation. They address critical areas of public health and have a significant impact on improving population health. The programs considered are briefly described below:

- Cancer Early Detection Program: This program focuses on the early detection of various forms of cancer through screening and education programs. Its importance lies in increasing survival rates and reducing the incidence of the disease.
- Contagious Disease Control Program: This program is dedicated to the prevention and control of infectious diseases, such as HIV/AIDS and sexually transmitted diseases, which is essential for public health and outbreak prevention.
- Physical Activity Promotion Program: This program encourages the incorporation of regular exercise and physical activity into daily life. Its impact is related to the prevention of obesity, cardiovascular diseases, and musculoskeletal disorders.
- Tobacco and Alcohol Prevention Program: This program aims to educate the population about the risks associated with tobacco and alcohol consumption. It also provides support to those who want to stop these habits, which can prevent respiratory diseases, cancer, and liver disorders.
- Maternal and Child Health Program: This program focuses on providing quality prenatal care, birth support, and early pediatric care. Its objective is to guarantee the health of mothers and babies while preventing complications related to pregnancy and childbirth.
- Mental Health and Wellness Program: This program addresses mental health and provides psychological support services. Its relevance lies in the prevention of mental illnesses, such as depression and anxiety, which have a significant impact on quality of life.
- Vector-Borne Disease Prevention Program: In regions where vector-borne diseases, such as malaria and dengue, are a threat, this program focuses on vector control to prevent outbreaks and protect the health of the population.
- Sexual and Reproductive Health Education Program: This program promotes safe sexual practices and provides access to contraceptives. Its focus addresses the prevention of unwanted pregnancies and sexually transmitted diseases.
- Nutrition Education Program: This program focuses on promoting the adoption of healthy eating habits and the control of obesity. Its importance lies in the prevention of chronic diseases, such as type 2 diabetes, cardiovascular diseases, and certain types of cancer, which are strongly related to diet.

To carry out a study that allows effective prioritization and allocation of budget and resources among the nine-health promotion and disease prevention programs mentioned, it is essential to establish a solid evaluation framework. The evaluation will be based on scientific criteria that consider the importance and impact of each program. Each of these criteria has an assigned weight that reflects its level of importance in the overall evaluation. Below, six key criteria are proposed for the evaluation and prioritization of these programs:

- **Disease Burden**: This criterion will evaluate the disease burden associated with each program. The prevalence of the diseases that the program addresses will be considered, as well as their impact on quality of life and mortality (0.15).
- **Clinical Effectiveness**: The clinical effectiveness of each program will be evaluated in terms of its ability to prevent or control the target diseases. Scientific evidence of the effectiveness and efficiency of interventions will be used as criteria for prioritization (0.15).
- **Risk assessment:** Assess potential health risks and emerging threats. Prioritize programs that address significant and evolving risks (0.20).

- Equity in Access and Results: Equity will be an important criterion. It will be evaluated whether the programs take into account equity in access to health services and whether they reduce health disparities in the population, especially among vulnerable groups (0.15).
- **Sustainability and Feasibility**: The long-term sustainability of each program will be considered, including the ability to sustain interventions over time (0.15).
- **Community Participation and Acceptance**: Active community participation and acceptance of the programs will be key criteria. Programs that involve the community and have a high level of acceptance among beneficiaries will be prioritized (0.20).

It is important to note that these weights reflect the relative importance of each criterion in the evaluation and prioritization process. In addition, the five experts participating in the study have equal weight and importance in decision-making, which guarantees an equitable and consensual approach in the allocation of resources and budget to the selected programs.

The individuals responsible for decision-making proceed to evaluate the identified alternatives, carefully considering each of the criteria previously selected for evaluation. To carry out this process, a transformation of the individual decision matrices of each expert is carried out, applying Eq. (2) to obtain matrix A. This matrix, whose details are presented in Table 2, represents the consolidation of individual evaluations carried out by experts in relation to the alternatives under consideration and the criteria established for the evaluation.

	Criterion 1	Criterion 2	Criterion 3	Criterion 4	Criterion 5	Criterion 6
A1	(0.020;0.979;0.97)	(0.242;0.757;0.724)	(0.082;0.944;0.956)	(0.08;0.94;0.95)	(0.08;0.94;0.95)	(0.08;0.94;0.95)
A2	(0.082;0.94;0.95)	(0.02;0.979;0.979)	(0.36;0.63;0.63)	(0.36;0.63;0.63)	(0.36;0.63;0.6)	(0.36;0.63;0.63)
A3	(0.369;0.630;0.63)	(0.36;0.630;0.630)	(0.369;0.63;0.630)	(0.36;0.63;0.63)	(0.36;0.63;0.63)	(0.36;0.63;0.6)
A4	(0.369.63;0.63)	(0.242;0.75;0.72)	(0.242;0.75;0.724)	(0.24;0.75;0.72)	(0.24;0.75;0.72)	(0.24;0.75;0.72)
A5	(0.242;0.75;0.72)	(0.129;0.87;0.87)	(0.129;0.87;0.87)	(0.12;0.87;0.87)	(0.12;0.87;0.87)	(0.12;0.87;0.87)
A6	(0.129;0.87;0.87)	(0.242;0.75;0.724)	(0.369;0.630;0.630)	(0.36;0.63;0.631)	(0.36;0.6;0.631)	(0.36;0.63;0.63)
A7	(0.369;0.630;0.63)	(0.242;0.757;0.724)	(0.242;0.757;0.724)	(0.24;0.75;0.7)	(0.24;0.75;0.72)	(0.24;0.75;0.72)
A8	(0.242;0.757;0.72)	(0.12;0.870;0.870)	(0.129;0.870;0.870)	(0.1294;0.87;0.8)	(0.12;0.87;0.87)	(0.12;0.87;0.87)
A9	(0.12;0.87;0.87)	(0.242;0.757;0.72)	(0.369;0.630;0.630)	(0.369;0.63;0.631)	(0.36;0.63;0.63)	(0.36;0.63;0.6)

 Table 2. Normalized decision matrix.

The next step is to determine the matrices that reflect the degrees of preference Pj (Bi, Br) in relation to the attribute Gj. These degrees of preference are calculated using the linear function proposed in Eq. (4), in which it is assumed that the parameters q = 1 and p = 0. Eq. (6) is used to calculate the integral priority index, and the Results are presented visually in the following matrix.

	г0.000	0.317	0.427	0.319	0.165	0.344	0.319	0.165	0.344 ן
	0.065	0.000	0.175	0.152	0.092	0.092	0.152	0.092	0.092
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	0.000				0.000	0.084	0.000	0.000	0.084
$\Pi =$	0.036	0.216	0.299	0.191	0.000	0.252	0.191	0.000	0.252
	0.000	0.000	0.083	0.060	0.036	0.000	0.060	0.036	0.000
	0.000		0.108			0.084		0.000	0.084
	0.036	0.216	0.299	0.191	0.000	0.252	0.191	0.000	0.252
	L0.000	0.000	0.083	0.060	0.036	0.000	0.060	0.036	0.000]

This information provides the inflow, outflow, and net flow for each of the alternatives, as detailed in Table 3. These flows are essential to understanding the prioritization and allocation of resources to health promotion and disease prevention programs under study.

Selection alternatives	φ +	φ-	ϕ
Cancer Early Detection Program	1	0.000	1,000
Contagious Disease Control Program	0.398	0.539	-0.142
Physical Activity Promotion Program	0	1,000	-1,000
Tobacco and Alcohol Prevention Program	0.135	0.578	-0.444
Maternal and Child Health Program	0.576	0.133	0.444
Mental Health and Wellness Program	0.134	0.672	-0.538
Vector-borne Disease Prevention Program	0.135	0.578	-0.444
Sexual and Reproductive Health Education Program	0.576	0.133	0.444
Nutrition Education Program	0.134	0.672	-0.538

Table 3. Inflows, outflows, and net flows for each alternative.

Table 3 presents the results of the evaluation of nine health and prevention programs through the calculation of the Φ index (phi), which is used as the main criterion for the classification of the alternatives. Each program has been evaluated based on the criteria described above for the allocation of resources in health promotion and disease prevention.

When observing the results, it can be noted that the "Cancer Early Detection Program" obtained the highest score in Φ with a value of 1, indicating that this program is considered the best alternative in terms of benefits. This suggests that the cancer early detection program is highly effective in cancer prevention and should therefore receive a high priority in resource allocation.

On the other hand, the "Physical Activity Promotion Program" obtained the lowest value in Φ - with -1, which means that it is the least favorable alternative in terms of costs associated with decision-making. This could indicate that the Physical Activity Promotion Program is less effective compared to the other programs and could require a review in terms of its efficiency and effectiveness.

The other programs are located in intermediate positions, reflecting different degrees of effectiveness and efficiency depending on the evaluated criteria. Some programs such as the "Maternal and Child Health Program" and the "Sexual and Reproductive Health Education Program" score higher on Φ + than on Φ -, suggesting that they offer significant benefits compared to their costs.

5 | Conclusions

Optimal allocation of resources to health promotion and disease prevention programs is a major challenge in healthcare management. During the study carried out, it was possible to validate the importance and effectiveness of neutrosophic logic in decision-making on the allocation of resources to health promotion and disease prevention programs. To this end, a comprehensive evaluation of nine health promotion and disease prevention programs was carried out, using a multi-criteria decision method that took advantage of neutrosophic logic as an evaluation framework.

The Early Cancer Detection Program emerged as the most favorable alternative in terms of benefits and clinical effectiveness, highlighting its importance in the prevention and control of cancer. On the other hand, the physical activity promotion program was identified as less desirable compared to other programs, suggesting the need to consider its effects on decision-making. The other programs were in intermediate positions, with variations in their Φ + and Φ - scores, which indicates the diversity of factors to take into account when allocating resources. This study provided a rigorous, neutrosophic, logic-based approach to evaluating and prioritizing health promotion programs. The results provide valuable information for decision-

making in resource allocation. It has been shown that neutrosophic logic is an effective tool in decisionmaking in the field of public health.

Acknowledgments

The author is grateful to the editorial and reviewers, as well as the correspondent author, who offered assistance in the form of advice, assessment, and checking during the study period.

Author Contributaion

All authors contributed equally to this work.

Funding

This research has no funding source.

Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

References

- Majumder, P. (2023). An integrated trapezoidal fuzzy FUCOM with single-valued neutrosophic fuzzy MARCOS and GMDH method to determine the alternatives weight and its applications in efficiency analysis of water treatment plant. Expert Systems with Applications, 225, 120087. https://doi.org/10.1016/j.eswa.2023.120087.
- [2] Pereira Jr, J. G., Ekel, P. Y., Palhares, R. M., & Parreiras, R. O. (2015). On multicriteria decision making under conditions of uncertainty. Information Sciences, 324, 44-59. https://doi.org/10.1016/j.ins.2015.06.013.
- [3] Fang, R., Liao, H., Yang, J. B., & Xu, D. L. (2021). Generalised probabilistic linguistic evidential reasoning approach for multi-criteria decision-making under uncertainty. Journal of the Operational Research Society, 72(1), 130-144. https://doi.org/10.1080/01605682.2019.1654415.
- [4] Broekhuizen, H., Groothuis-Oudshoorn, C. G., van Til, J. A., Hummel, J. M., & IJzerman, M. J. (2015). A review and classification of approaches for dealing with uncertainty in multi-criteria decision analysis for healthcare decisions. Pharmacoeconomics, 33, 445-455. https://doi.org/10.1007/s40273-014-0251-x.
- [5] Abdelfattah, W. (2019). Data envelopment analysis with neutrosophic inputs and outputs. Expert Systems, 36(6), e12453. https://doi.org/10.1111/exsy.12453.
- [6] Xia, Z., Li, A., Feng, D., Li, J., Chen, X., & Zhou, G. (2021). Comparative analysis of typical mathematical modelling methods through model updating of a real-life bridge structure with measured data. Measurement, 174, 108987. https://doi.org/10.1016/j.measurement.2021.108987.
- [7] Khuman, A. S. (2021). The similarities and divergences between grey and fuzzy theory. Expert Systems with Applications, 186, 115812. https://doi.org/10.1016/j.eswa.2021.115812.
- [8] Debnath, S. (2022). Fuzzy quadripartitioned neutrosophic soft matrix theory and its decision-making approach. Journal of Computational and Cognitive Engineering, 1(2), 88-93. https://doi.org/10.47852/bonviewJCCE19522514205514.
- [9] El-Hefenawy, N., Metwally, M. A., Ahmed, Z. M., & El-Henawy, I. M. (2016). A review on the applications of neutrosophic sets. Journal of Computational and Theoretical Nanoscience, 13(1), 936-944. https://doi.org/10.1166/jctn.2016.4896.
- [10] Khan, M., Son, L. H., Ali, M., Chau, H. T. M., Na, N. T. N., & Smarandache, F. (2018). Systematic review of decision making algorithms in extended neutrosophic sets. Symmetry, 10(8), 314. https://doi.org/10.3390/sym10080314.

- [11] Leyva-Vázquez, M., & Smarandache, F. (2018). Inteligencia Artificial: retos, perspectivas y papel de la Neutrosofía. Infinite Study.
- [12] Khan, M. A., & Alghamdi, N. S. (2023). A neutrosophic WPM-based machine learning model for device trust in industrial internet of things. Journal of Ambient Intelligence and Humanized Computing, 14(4), 3003-3017. https://doi.org/10.1007/s12652-021-03431-2.
- [13] Fernández, A. R., Rosales, L. V. M., Paspuel, O. G. A., López, W. B. J., & León, A. R. S. (2021). Neutrosophic Statistics for Project Management. Application to a Computer System Project. Neutrosophic Sets and Systems, 44, 308-314.
- [14] Ansari, A. Q., Biswas, R., & Aggarwal, S. (2011). Proposal for applicability of neutrosophic set theory in medical AI. International Journal of Computer Applications, 27(5), 5-11.
- [15] Nguyen, G. N., Son, L. H., Ashour, A. S., & Dey, N. (2019). A survey of the state-of-the-arts on neutrosophic sets in biomedical diagnoses. International Journal of Machine Learning and Cybernetics, 10, 1-13. https://doi.org/10.1007/s13042-017-0691-7.
- [16] Marsh, K., Lanitis, T., Neasham, D., Orfanos, P., & Caro, J. (2014). Assessing the value of healthcare interventions using multi-criteria decision analysis: a review of the literature. Pharmacoeconomics, 32(4), 345-365. https://doi.org/10.1007/s40273-014-0135-0.
- [17] Xu, D., Wei, X., Ding, H., & Bin, H. (2020). A new method based on PROMETHEE and TODIM for multi-attribute decision-making with single-valued neutrosophic sets. Mathematics, 8(10), 1816. https://doi.org/10.3390/math8101816.
- [18] Salmeron, J. L., & Smarandache, F. (2008). Redesigning Decision Matrix Method with an indeterminacy-based inference process. International Journal of Applied Mathematics & Statistics, 13(M 08), 4-11.
- [19] Biswas, P., Pramanik, S., & Giri, B. C. (2016). TOPSIS method for multi-attribute group decision-making under single-valued neutrosophic environment. Neural computing and Applications, 27, 727-737. https://doi.org/10.1007/s00521-015-1891-2.
- [20] Zou, J., Deng, Y., Hu, Y., & Lin, G. (2018). Measure distance between neutrosophic sets: An evidential approach. Infinite Study.
- [21] Ramos Sánchez, R. E., Ramos Solorzano, R. X., & Estupiñán Ricardo, J. (2021). La transformación de los objetivos de desarrollo sostenible desde una dinámica prospectiva y operativa de la Carrera de Derecho en Uniandes en época de incertidumbre. Conrado, 17(81), 153-162.
- [22] Estupiñán Ricardo, J., Leyva Vázquez, M. Y., Marcial Coello, C. R., & Figueroa Colin, S. E. (2021). Importancia de la preparación de los académicos en la implementación de la investigación científica. Conrado, 17(82), 337-343.

Disclaimer/Publisher's Note: The perspectives, opinions, and data shared in all publications are the sole responsibility of the individual authors and contributors, and do not necessarily reflect the views of Sciences Force or the editorial team. Sciences Force and the editorial team disclaim any liability for potential harm to individuals or property resulting from the ideas, methods, instructions, or products referenced in the content.