



A Group Decision Making Framework Based on Neutrosophic TOPSIS Approach for Smart Medical Device Selection

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Received: 15 November 2018 / Accepted: 4 January 2019 / Published online: 10 January 2019
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Abstract

Advances in the medical industry has become a major trend because of the new developments in information technologies. This research offers a novel approach for estimating the smart medical devices (SMDs) selection process in a group decision making (GDM) in a vague decision environment. The complexity of the selected decision criteria for the smart medical devices is a significant feature of this analysis. To simulate these processes, a methodology that combines neutrosophics using bipolar numbers with Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) under GDM is suggested. Neutrosophics with TOPSIS approach is applied in the decision making process to deal with the vagueness, incomplete data and the uncertainty, considering the decisions criteria in the data collected by the decision makers (DMs). In this research, the stress is placed upon the choosing of sugar analyzing smart medical devices for diabetics' patients. The main objective is to present the complications of the problem, raising interest among specialists in the healthcare industry and assessing smart medical devices under different evaluation criteria. The problem is formulated as a multi criteria decision type with seven alternatives and seven criteria, and then edited as a multi criteria decision model with seven alternatives and seven criteria. The results of the neutrosophics with TOPSIS model are analyzed, showing that the competence of the acquired results and the rankings are sufficiently stable. The results of the suggested method are also compared with the neutrosophic extensions AHP and MOORA models in order to validate and prove the acquired results. In addition, we used the SPSS program to check the stability of the variations in the rankings by the Spearman coefficient of correlation. The selection methodology is applied on a numerical case, to prove the validity of the suggested approach.

Keywords Bipolar neutrosophic numbers · Smart medical devices · Group decision making · TOPSIS method · Multi criteria decision making

This article is part of the Topical Collection on *Systems-Level Quality Improvement*

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Introduction

In the light of emerging digital technologies and their applications in medical systems, a rapid development is noticed in an extensive number of medical devices. The healthcare manufacture is revolutionizing how patients are cured by using technological advances. The leading factor of this transformation is based on evolutions in actuator and sensor technology, becoming more qualified in merging with electrical and chemical elements. Developments in Nano and micro technology make it easier for communicating with extrinsic systems, better data collecting, creating tools, devices and apparatuses helping medical staff as well as patients, more and better substances that can be vaccinated immediately into human body. These innovative ways of remediation help curing health cases outside of a healthcare facility. Minimally invasive or noninvasive small scale medical tools offer significant challenges to inspiring new smart and powerful devices. Portable devices today can accurately measure

the percentage of diabetes in the blood. Different medical tasks and abilities are performed by medical robots. Digitalization is revolutionizing the submission of healthcare services, both at hospitals and at home, by using surgical robots for help during more complex procedures or for simpler tasks, such as use a diabetes analyzer, management of medicines to patients. In the future, developed medical devices can possibly enable patients to connect healthcare services without the necessity of physically attend the hospitals. In addition, smartphone applications help patients to interact with medical devices connected to the patients, and help patients to remotely access these services. Instead of patients visiting medical staff and hospitals to measure percentage of diabetes in the blood, patients can use the portable devices to measure the percentage of diabetes in the blood at home, without discomfort and fatigue, especially after a breakthrough in the manufacture of portable a diabetes analyzer. Also, a diabetes analyzer can be connected to external smartphones for analyzing the results more accurately. As a response to this market growth of various devices of broad availability, the healthcare industry is actively following new ways on how to select those devices that best address the requirements of patients. Occasionally, the requirements can be uncertain, ambiguous and vague, as they are related with the expectations and demands of human beings. Thus, MDs can be selected based on decision criteria such as their accuracy, precision, and reliability. This study aims to suggest a set of valuation criteria for the healthcare industry in relationship to the selection and valuation of portable diabetes analyzer devices and their results. There are many resources that can be used for collecting the evaluation criteria, such as the judgments of academic experts, industrial and decision makers, the current scientific literature or available regulations. Decision making is mostly about choosing the preferable choice between a set of alternatives by considering the influence of many criteria altogether. In the last five decades, the multi criteria decision making (MCDM) methodology became one of the most important key in solving complicated and complex decision problems in the existence of multiple criteria and alternatives [1]. The MCDM methodology can be used to resolve multi valuation and ordering problems that combine a number of inconsistent criteria. After this progress, several types of MCDM methods are suggested to successfully solve various types of decision making problems. This powerful methodology often needs qualitative and quantitative data, which are used in the measurement of obtainable alternatives. In multi MCDM problems, interdependency, mutuality and interactivity features between decision criteria are of a vague nature, which obscures the task of a membership [2]. However, most methods proved inadequate and inappropriate in solving and explaining real life problems, mostly because they rely on crisp values. Many MCDM methods use the fuzzy or the intuitionistic fuzzy set theories to overcome this obstacle. Nevertheless, F and IF numbers are also not always appropriate. Classes of F and IF sets proved to be efficient in some implementations. Nevertheless, in

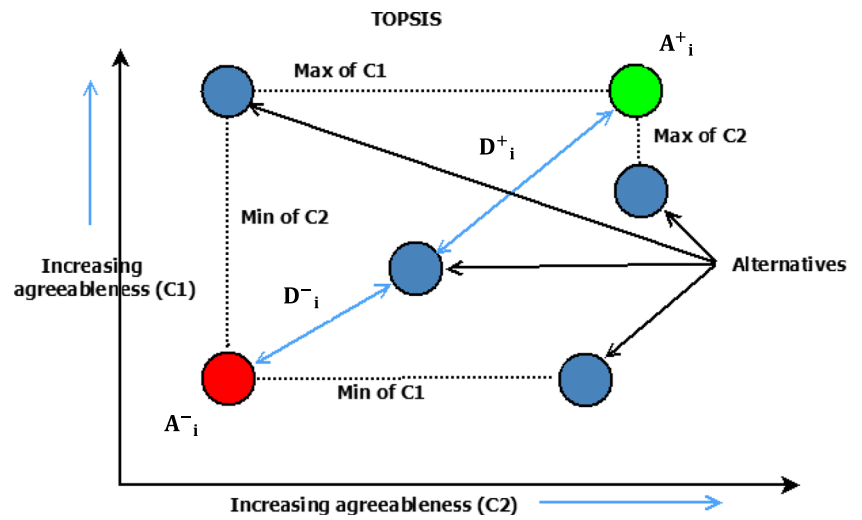
our opinion that is a compromise, since the Neutrosophic set offers major and better possibilities [3, 4]. The notion / concept of neutrosophic set provides a substitute approach where there is a lack of accuracy to the determinations imposed by the crisp sets or traditional fuzzy sets, and in situations where the presented information is not suitable to locate its inaccuracy. Neutrosophic sets are very powerful and successful in overcoming situations and cases in incomplete information environment, uncertainty, vagueness and imprecision, and it is described by a membership degree, an indeterminacy degree and a nonmembership degree [5]. Therefore, neutrosophic sets introduce a qualified tool for expressing DMs' preferences and priorities, completely determining the membership function in situations where DM opinions are subject to indeterminacy or lack of information. DMs use linguistic variables expressed in two parts, where the first part is employed to voice their preferences and the other part is used to convey the confirmation degree of linguistic variable according to each DM [6]. Neutrosophic set is becoming a scientific key tool, receiving attention from many DMs and academic researchers for developing and improving the neutrosophic methodology [7–9]. Many decision problems faced in life require the contribution of more than one DM in the decision making processes. Thus, most of MCDM methods are also extended to GDM. The key advantage of Neutrosophic sets over the crisp or fuzzy and IFs is their capability to present the positive and the negative designation of an element's value on membership, indeterminacy membership and nonmembership in the sets. When DMs express their views and opinions, they generally rely on information about more criteria and more alternatives that become more complicated. To overcome these situations, a widely accepted MCDM method is the TOPSIS method with a major advantage due to its simplicity and ability to consider a non-limited number of alternatives and criteria in the decision making process [10]. Hence, using TOPSIS is very effective in finding the expected utility of an uncertain situation, incomplete information and vagueness. TOPSIS method defines a solution at the shortest distance to the ideal solution and the greatest distance from the negative-ideal solution, but it does not reflect the proportional significance of these distances, as indicated in Fig. 1.

The main accomplishments of this research are:

- The characterization and preparation of an effective evaluation framework to lead the medical industry towards the suitable smart medical device selection.
- It also contributes to the literature by providing a novel Neutrosophic with TOPSIS method under GDM setting, by considering the interactions among medical device selection criteria in a vague environment.

The structure of this research is summarized as follows. In section 2, a review of related publications is given. Section 3 provides an introduction to the bipolar neutrosophic numbers

Fig. 1 The ideal solution of TOPSIS method

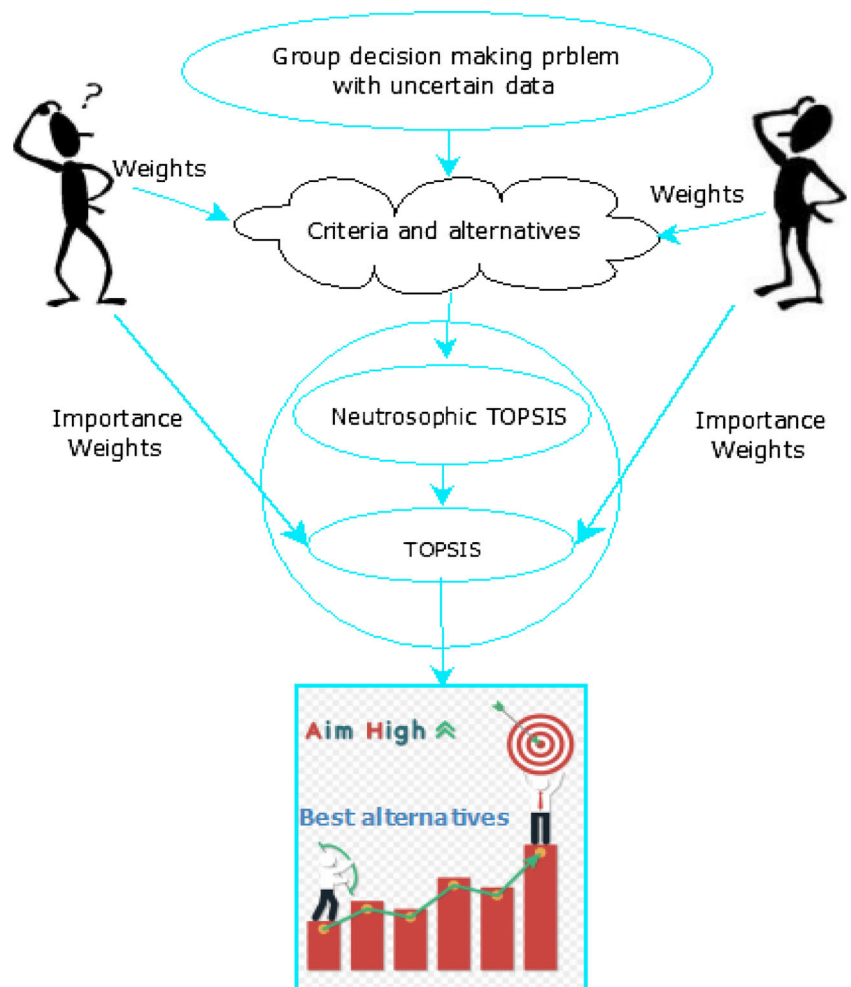


and to the steps of the suggested method. Section 4 gives a detailed commentary of the alternatives and evaluation criteria in a numerical experiment, in which diabetes analyzer devices are selected to present the execution of the applied method. Finally, we close our research with some remarks.

Literature Review

Decision making in real life situations is the means of selecting the best candidate from several options. DMs need to consider multiple criteria in order to evaluate the best

Fig. 2 The general conceptualization of the suggested method



candidate. MCDM methods are recognized by scholars since the early 1970s. In situation of multiple criteria or goals, MCDM methods include essential area of research to transact with complex problems. Many MCDM methods with characteristic features have been suggested in the literature, such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [11], Analytic Hierarchy Process (AHP) [12], Multi Objective Optimization on the basis of Ratio

Analysis (MOORA) [13, 14]. Many types of MCDM approaches have been successfully implemented to various types of decision making problems. As these methods mostly work with crisp sets, they have been seen imperfect to deal with many decisions problems. Also, the task of identifying the best alternative becomes more challenging for a DM, as decision making gets more complex. Many such mechanisms are successfully extended to other environments. In the last two

Fig. 3 Diagram of the Neutrosophic with TOPSIS method

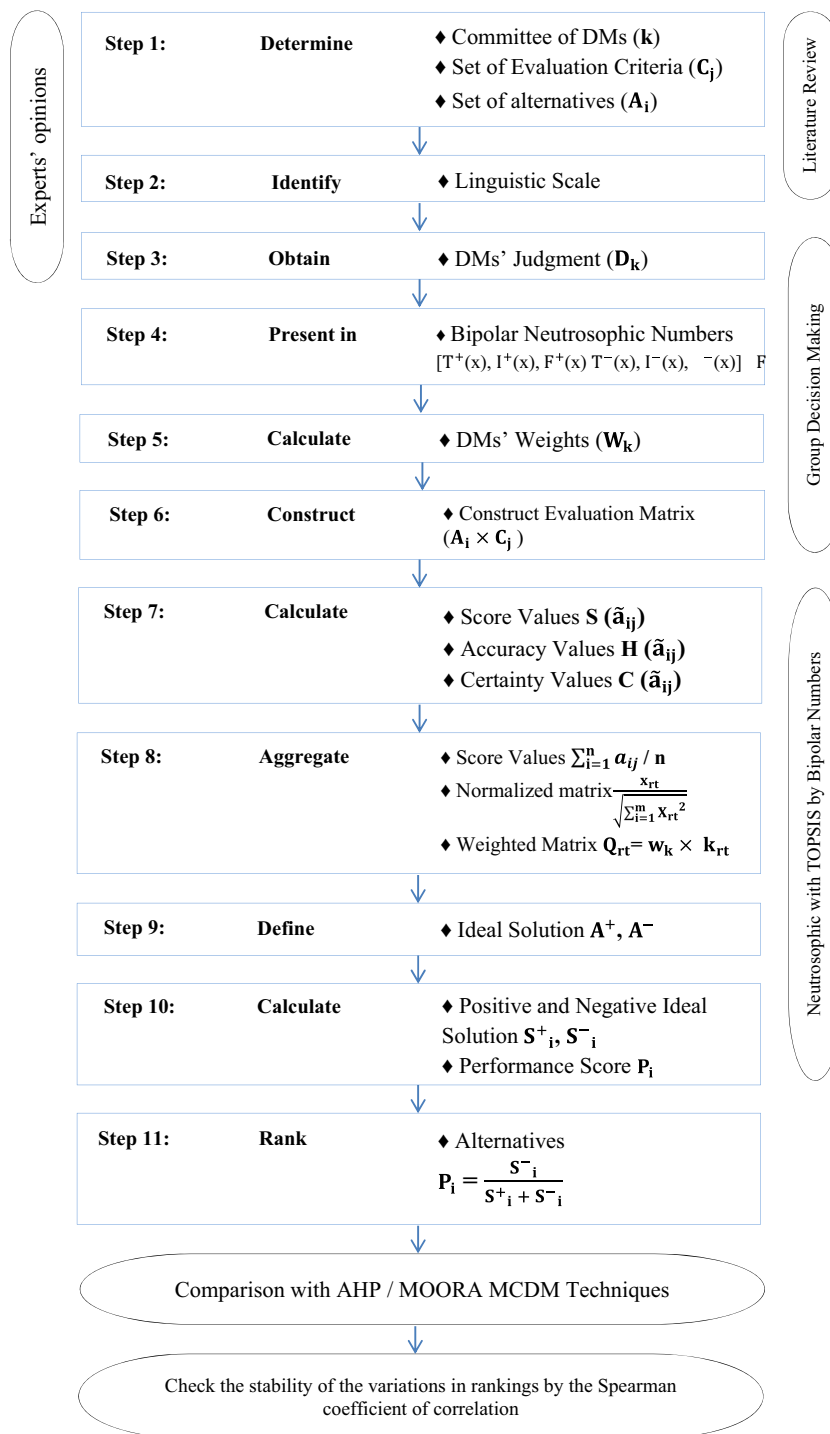
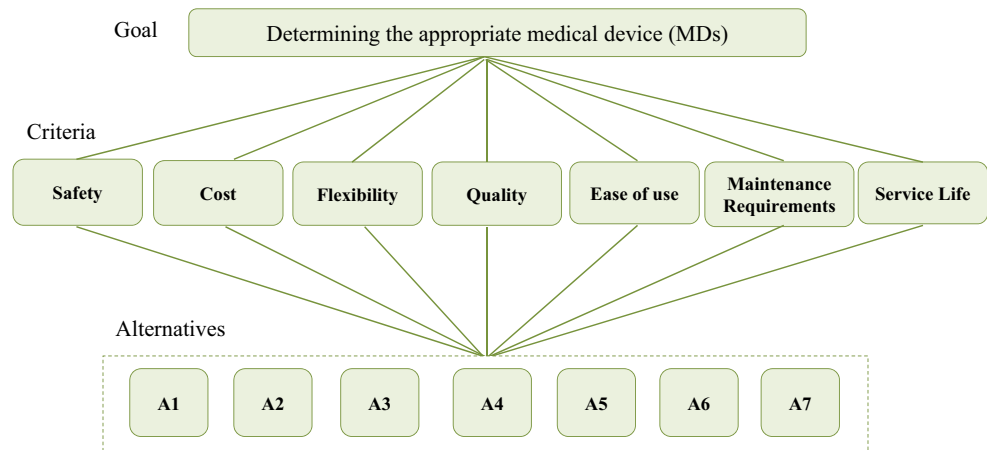


Fig. 4 The hierarchy for selecting the appropriate medical device



decades, most studies in literature apply the fuzzy and IFs theory due to its similarity to human reasoning [15, 16]. Following that, Smarandache introduced the concept of neutrosophic set, which is the generalization of Atanassov IFs, where to each element of the set is attributed a membership value, an indeterminacy value and a membership value [17]. Various types of MCDM approaches are integrated by neutrosophic set. When compared to IFs, neutrosophic sets have many advantages. Consequently, it is extensively studied by many academics [18–27]. The specific method in this study is presented in detail in the next section.

Methodology

The purpose of the suggested technique is to incubate a conceptual framework for valuation of sugar analyzing smart medical devices for diabetics’ patients with consideration to predefined objectives. The following subsection comments on neutrosophic and TOPSIS, respectively. Then, the suggested method is presented.

Preliminaries

In this subsection, we give the basic definitions of neutrosophic set and bipolar neutrosophic numbers (BNNs).

Bipolar Neutrosophic Set (BNS)

We give the definition of bipolar neutrosophic set (BNS), and discuss some of its properties, including certainty, score and accuracy functions [28–32].

Definition 2.1.1.1 A bipolar neutrosophic set A in X is defined as an object of the form $A = \{ \langle x, T^+(x), I^+(x), F^+(x), T^-(x), I^-(x), F^-(x) \rangle : x \in X \}$, where $T^+, I^+, F^+ : X \rightarrow [1, 0]$ and $T^-, I^-, F^- : X \rightarrow [-1, 0]$. The positive membership degree $T^+(x), I^+(x), F^+(x)$ denotes the truth membership, the indeterminate

membership and the false membership of an element $x \in X$ corresponding to a bipolar neutrosophic set A, and the negative membership degree $T^-(x), I^-(x), F^-(x)$ denotes the truth membership, the indeterminate membership and the false membership of an element $x \in X$ to some implicit counter property corresponding to a bipolar neutrosophic set A.

Definition 2.1.1.2 Let $A_1 = \{ \langle x, T_1^+(x), I_1^+(x), F_1^+(x), T_1^-(x), I_1^-(x), F_1^-(x) \rangle$ and $A_2 = \{ \langle x, T_2^+(x), I_2^+(x), F_2^+(x), T_2^-(x), I_2^-(x), F_2^-(x) \rangle$ be two bipolar neutrosophic sets. Then, their union is defined as: $(A_1 \cup A_2)(x) = (\max(T_1^+(x), T_2^+(x)), \frac{I_1^+(x) + I_2^+(x)}{2}, \min((F_1^+(x), F_2^+(x)), \min(T_1^-(x), T_2^-(x)), \frac{I_1^-(x) + I_2^-(x)}{2}, \max((F_1^-(x), F_2^-(x))))$, for all $x \in X$.

Definition 2.1.1.3 Let $\tilde{a}_1 = (T_1^+, I_1^+, F_1^+, T_1^-, I_1^-, F_1^-)$ and $\tilde{a}_2 = (T_2^+, I_2^+, F_2^+, T_2^-, I_2^-, F_2^-)$ be two bipolar neutrosophic numbers. Then, the operations for NNs are defined as below:

- i. $\lambda \tilde{a}_1 = (1 - (1 - T_1^+)^{\lambda}, (I_1^+)^{\lambda}, (F_1^+)^{\lambda}, -(-T_1^-)^{\lambda}, -(-I_1^-)^{\lambda}, -(1 - (1 - F_1^-)^{\lambda}))$
- ii. $\tilde{a}_1^{\lambda} = ((T_1^+)^{\lambda}, 1 - (1 - I_1^+)^{\lambda}, 1 - (1 - F_1^+)^{\lambda}, -(1 - (1 - T_1^-)^{\lambda}), -(I_1^-)^{\lambda}, -(-F_1^-)^{\lambda})$
- iii. $\tilde{a}_1 + \tilde{a}_2 = (T_1^+ + T_2^+ - T_1^+ T_2^+, I_1^+ I_2^+, F_1^+ F_2^+, -T_1^- T_2^-, -(-I_1^- - I_2^- - I_1^- I_2^-), -(-F_1^- - F_2^- - F_1^- F_2^-))$

Table 1 Criteria weights according to all decision makers

DMs	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇
DM ₁	⟨VG⟩	⟨EB⟩	⟨P⟩	⟨EG⟩	⟨VG⟩	⟨B⟩	⟨AS⟩
DM ₂	⟨P⟩	⟨AS⟩	⟨MB⟩	⟨AS⟩	⟨MG⟩	⟨AS⟩	⟨EB⟩
DM ₃	⟨MB⟩	⟨B⟩	⟨VB⟩	⟨P⟩	⟨VB⟩	⟨MG⟩	⟨P⟩
DM ₄	⟨EG⟩	⟨MG⟩	⟨AS⟩	⟨VG⟩	⟨MB⟩	⟨EG⟩	⟨EG⟩

Table 2 Criteria weights according to all decision makers by bipolar neutrosophic numbers

Criteria	DM ₁	DM ₂	DM ₃	DM ₄
C ₁	[1.0,0.0,0.1, -0.3, -0.8, -0.9]	[0.7,0.6,0.5, -0.2, -0.5, -0.6]	[0.3, 0.1, 0.9, -0.4, -0.2, -0.1]	[0.9, 0.1, 0.0, 0.0, -0.8, -0.9]
C ₂	[0.1, 0.9, 0.8, -0.9, -0.2, -0.1]	[0.5, 0.2, 0.3, -0.3, -0.1, -0.3]	[0.4, 0.4, 0.3, -0.5, -0.2, -0.1]	[0.8, 0.5, 0.6, -0.1, -0.8, -0.9]
C ₃	[0.7,0.6,0.5, -0.2, -0.5, -0.6]	[0.3, 0.1, 0.9, -0.4, -0.2, -0.1]	[0.2, 0.3, 0.4, -0.8, -0.6, -0.4]	[0.5, 0.2, 0.3, -0.3, -0.1, -0.3]
C ₄	[0.9, 0.1, 0.0, 0.0, -0.8, -0.9]	[0.5, 0.2, 0.3, -0.3, -0.1, -0.3]	[0.7,0.6,0.5, -0.2, -0.5, -0.6]	[1.0,0.0,0.1, -0.3, -0.8, -0.9]
C ₅	[1.0,0.0,0.1, -0.3, -0.8, -0.9]	[0.8, 0.5, 0.6, -0.1, -0.8, -0.9]	[0.2, 0.3, 0.4, -0.8, -0.6, -0.4]	[0.3, 0.1, 0.9, -0.4, -0.2, -0.1]
C ₆	[0.4, 0.4, 0.3, -0.5, -0.2, -0.1]	[0.5, 0.2, 0.3, -0.3, -0.1, -0.3]	[0.8, 0.5, 0.6, -0.1, -0.8, -0.9]	[0.9, 0.1, 0.0, 0.0, -0.8, -0.9]
C ₇	[0.5, 0.2, 0.3, -0.3, -0.1, -0.3]	[0.1, 0.9, 0.8, -0.9, -0.2, -0.1]	[0.7,0.6,0.5, -0.2, -0.5, -0.6]	[0.9, 0.1, 0.0, 0.0, -0.8, -0.9]

iv. $\tilde{a}_1.\tilde{a}_2 = (T_1^+ T_2^+, I_1^+ + I_2^+ - I_1^- I_2^+ + F_1^+ + F_2^+ - F_1^- F_2^+, -(-T_1^- - T_2^- - T_1^- T_2^-), -I_1^- I_2^-, -F_1^- F_2^-)$, where $\lambda > 0$.

Definition 2.1.1.4 Let $\tilde{a}_1 = (T_1^+, I_1^+, F_1^+, T_1^-, I_1^-, F_1^-)$ be a bipolar neutrosophic number. Then, the score function $s(\tilde{a}_1)$, accuracy function $a(\tilde{a}_1)$ and certainty function $c(\tilde{a}_1)$ of an NBN are defined as follows:

$$\tilde{s}(\tilde{a}_1) = (T_1^+ + 1 - I_1^+ + 1 - F_1^+ + 1 + T_1^- - I_1^- - F_1^-) / 6 \quad (1)$$

$$\tilde{a}(\tilde{a}_1) = T_1^+ - F_1^+ + T_1^- - F_1^- \quad (2)$$

$$\tilde{c}(\tilde{a}_1) = T_1^+ - F_1^- \quad (3)$$

Definition 2.1.1.5 Let $\tilde{a}_1 = (T_1^+, I_1^+, F_1^+, T_1^-, I_1^-, F_1^-)$ and $\tilde{a}_2 = (T_2^+, I_2^+, F_2^+, T_2^-, I_2^-, F_2^-)$ be two bipolar neutrosophic numbers. The comparison method can be defined as follows:

- i. if $\tilde{s}(\tilde{a}_1) > \tilde{s}(\tilde{a}_2)$, then \tilde{a}_1 is greater than \tilde{a}_2 , that is, \tilde{a}_1 is superior to \tilde{a}_2 , denoted by $\tilde{a}_1 > \tilde{a}_2$
- ii. $\tilde{s}(\tilde{a}_1) = \tilde{s}(\tilde{a}_2)$ and $\tilde{a}(\tilde{a}_1) > \tilde{a}(\tilde{a}_2)$, then \tilde{a}_1 is greater than \tilde{a}_2 , that is, \tilde{a}_1 is superior to \tilde{a}_2 , denoted by $\tilde{a}_1 < \tilde{a}_2$;
- iii. if $\tilde{s}(\tilde{a}_1) = \tilde{s}(\tilde{a}_2)$, $\tilde{a}(\tilde{a}_1) = \tilde{a}(\tilde{a}_2)$ and $\tilde{c}(\tilde{a}_1) > \tilde{c}(\tilde{a}_2)$, then \tilde{a}_1 is greater than \tilde{a}_2 , that is, \tilde{a}_1 is superior to \tilde{a}_2 , denoted by $\tilde{a}_1 > \tilde{a}_2$;
- iv. if $\tilde{s}(\tilde{a}_1) = \tilde{s}(\tilde{a}_2)$, $\tilde{a}(\tilde{a}_1) = \tilde{a}(\tilde{a}_2)$ and $\tilde{c}(\tilde{a}_1) = \tilde{c}(\tilde{a}_2)$, then \tilde{a}_1 is equal to \tilde{a}_2 , that is, \tilde{a}_1 is indifferent to \tilde{a}_2 , denoted by $\tilde{a}_1 = \tilde{a}_2$.

Definition 2.1.1.6 Let $\tilde{a}_j = (T_j^+, I_j^+, F_j^+, T_j^-, I_j^-, F_j^-)$ ($j = 1, 2, \dots, n$) be a family of bipolar neutrosophic numbers. A mapping $A_w: Q_n \rightarrow Q$ is called bipolar neutrosophic weighted average operator if it satisfies the condition:

$$A_w(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{j=1}^n \omega_j \tilde{a}_j = \left(1 - \prod_{j=1}^n (1 - T_j^+)^{\omega_j}, \prod_{j=1}^n I_j^{+\omega_j}, \prod_{j=1}^n F_j^{+\omega_j}, -\prod_{j=1}^n (-T_j^-)^{\omega_j}, -1 \left(\prod_{j=1}^n (1 - (-I_j^-))^{\omega_j} \right), - \left(1 - \prod_{j=1}^n (1 - (-F_j^-))^{\omega_j} \right) \right),$$

where ω_j is the weight of \tilde{a}_j ($j = 1, 2, \dots, n$), $\omega_j \in [0, 1]$ and $\sum_{j=1}^n \omega_j = 1$.

The Suggested Method Procedure

In this section, the steps of the suggested bipolar neutrosophic with TOPSIS framework are presented in details, and the general conceptualization of the framework is exposed in Fig. 2.

The suggested framework consists of many steps, see Fig. 3 below.

Step 1. Organize a committee of DMs and determine the goal, the alternatives and the valuation criteria.

Suppose that DMs want to appreciate the collection of n criteria and m alternatives. DMs are symbolized by $D_E = \{DM_1, DM_2, DM_3, DM_4\}$, where $E = 1, 2, \dots, E$, and alterna-

Table 3 The normalized criteria weights

Weight \tilde{w}_n	Aggregation weights in BNNs	crisp	Normalized Weight
C ₁	[0.725, 0.2, 0.375, -0.225, -0.575, -0.625]	0.6875	0.17
C ₂	[0.450, 0.50, 0.500, -0.45, -0.325, -0.35]	0.4458	0.09
C ₃	[0.425, 0.3, 0.525, -0.425, -0.350, -0.350]	0.4792	0.11
C ₄	[0.775, 0.225, 0.225, -0.20, -0.55, -0.675]	0.7250	0.21
C ₅	[0.575, 0.225, 0.500, -0.4, -0.600, -0.575]	0.6042	0.14
C ₆	[0.650, 0.300, 0.3, -0.225, -0.475, -0.550]	0.6417	0.15
C ₇	[0.550, 0.450, 0.40, -0.35, -0.400, -0.475]	0.5375	0.13

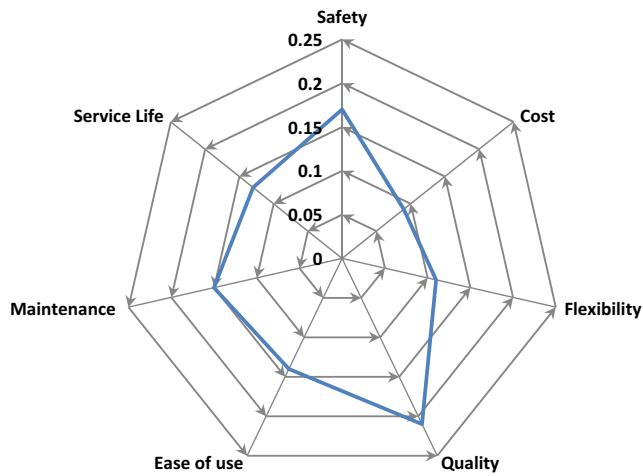


Fig. 5 Criteria weights according to all decision makers

Table 5 The aggregated crisp values of decision matrix

C_n/A_n	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ϕ_1	0.48	0.69	0.5	0.64	0.55	0.51	0.82
ϕ_2	0.53	0.73	0.55	0.67	0.51	0.84	0.69
ϕ_3	0.85	0.48	0.63	0.54	0.61	0.63	0.76
ϕ_4	0.47	0.38	0.66	0.60	0.64	0.64	0.29
ϕ_5	0.65	0.69	0.78	0.57	0.42	0.68	0.75
ϕ_6	0.76	0.44	0.44	0.56	0.77	0.39	0.22
ϕ_7	0.53	0.51	0.77	0.49	0.39	0.68	0.64

Step 2. Depict and design the linguistic scales to describe DMs, and set the alternatives.

Step 3. Obtain DMs' judgments on each element.

tives by $A_i = \{A_1, A_2, \dots, A_m\}$, where $i = 1, 2, \dots, m$, assessed on n criteria $c_j = \{c_1, c_2, \dots, c_n\}$, $j = 1, 2, \dots, n$.

Based on previously knowledge and experience, DMs are demanded to convey their judgments. Every DM gives his / her judgment on every of these elements.

Table 4 Ratings of alternatives and criteria by DMs

DMs	Alternatives	C_1	C_2	C_3	C_4	C_5	C_6	C_7
DM ₁	ϕ_1	(P)	(MB)	(EG)	(EB)	(AS)	(VB)	(VG)
	ϕ_2	(EB)	(VG)	(P)	(B)	(VG)	(P)	(MG)
	ϕ_3	(EG)	(AS)	(MB)	(VG)	(P)	(MG)	(EG)
	ϕ_4	(AS)	(B)	(MG)	(VB)	(MB)	(EG)	(EB)
	ϕ_5	(EG)	(P)	(EG)	(EB)	(AS)	(VG)	(B)
	ϕ_6	(VG)	(B)	(AS)	(EG)	(EG)	(MB)	(VB)
	ϕ_7	(EB)	(MB)	(VG)	(MB)	(EB)	(EG)	(VG)
DM ₂	ϕ_1	(MB)	(VG)	(VB)	(P)	(MG)	(EB)	(EG)
	ϕ_2	(AS)	(P)	(MB)	(EG)	(EB)	(EG)	(AS)
	ϕ_3	(MG)	(EG)	(AS)	(MG)	(MG)	(MG)	(VG)
	ϕ_4	(EB)	(VB)	(EB)	(EG)	(VG)	(EG)	(MB)
	ϕ_5	(MB)	(EG)	(VG)	(MB)	(VB)	(B)	(MG)
	ϕ_6	(VG)	(MG)	(MG)	(P)	(AS)	(EB)	(VB)
	ϕ_7	(P)	(AS)	(MG)	(EG)	(MG)	(MG)	(MG)
DM ₃	ϕ_1	(B)	(EG)	(P)	(EG)	(VB)	(EG)	(P)
	ϕ_2	(MG)	(EG)	(MB)	(B)	(VG)	(EG)	(EG)
	ϕ_3	(VG)	(EB)	(EG)	(B)	(VB)	(MB)	(VG)
	ϕ_4	(AS)	(MG)	(VG)	(MG)	(MB)	(EB)	(AS)
	ϕ_5	(MB)	(AS)	(MG)	(EG)	(AS)	(VG)	(EG)
	ϕ_6	(EG)	(VB)	(MB)	(AS)	(EG)	(EG)	(EB)
	ϕ_7	(VG)	(B)	(P)	(EB)	(EB)	(MB)	(P)
DM ₄	ϕ_1	(AS)	(P)	(VB)	(EG)	(MG)	(MG)	(VG)
	ϕ_2	(MG)	(AS)	(VG)	(EG)	(EB)	(EG)	(P)
	ϕ_3	(VG)	(MB)	(MG)	(EB)	(VG)	(MG)	(MB)
	ϕ_4	(MG)	(EB)	(EG)	(AS)	(EG)	(P)	(EB)
	ϕ_5	(EG)	(MG)	(P)	(VG)	(MB)	(AS)	(EG)
	ϕ_6	(MB)	(MB)	(EB)	(VB)	(MG)	(EB)	(VB)
	ϕ_7	(AS)	(MG)	(VG)	(AS)	(P)	(MG)	(MB)

Table 6 The normalized decision matrix

C_n/A_n	C_1	C_2	C_3	C_4	C_5	C_6	C_7
ϕ_1	0.30	0.43	0.31	0.40	0.34	0.32	0.51
ϕ_2	0.31	0.42	0.32	0.39	0.29	0.48	0.40
ϕ_3	0.49	0.28	0.36	0.31	0.35	0.36	0.44
ϕ_4	0.33	0.26	0.46	0.42	0.45	0.45	0.20
ϕ_5	0.37	0.40	0.45	0.33	0.24	0.39	0.43
ϕ_6	0.53	0.31	0.31	0.39	0.53	0.27	0.15
ϕ_7	0.34	0.33	0.50	0.32	0.25	0.44	0.41

- a. Collect the judgments of DMs about each other and from the viewpoint of the Kth DM
- b. Gather the judgments on all the alternatives for every criterion from the viewpoint of the Kth DM.

Step 4. Obtain the conversion of (BNNs) bipolar neutrosophic numbers.

When all DMs give their valuations on each element, the bipolar neutrosophic values preference scale in subsection 3.2 is used.

- a. Transforming DMs’ linguistic valuations into bipolar neutrosophic numbers for every DM provides judgment with assistance of the linguistic weighting terms as shown in subsection 3.2.
- b. Building the preference relation matrix with the assistance of BNNs to determine weights of criteria. DMs use the linguistic terms shown in subsection 3.2 to evaluate their opinions with respect to each criterion. Let R^{k}_{ij} be a (BN) decision matrix of the Kth DMs for calculating weights of criteria by opinions of DMs, then:

$$R^{k}_{ij} = \begin{bmatrix} r^{k}_{11} & \dots & r^{k}_{1n} \\ \vdots & \ddots & \vdots \\ r^{k}_{m1} & \dots & r^{k}_{mn} \end{bmatrix}, k \in K \tag{4}$$

where $r^{k}_{ij} = [T^+(x), I^+(x), F^+(x), T^-(x), \Gamma(x), F^-(x)]$, $k = 1, 2, \dots, K, i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Table 7 The weighted matrix

C_n/A_n	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Weight	0.17	0.09	0.11	0.21	0.14	0.15	0.13
ϕ_1	0.051	0.039	0.034	0.084	0.048	0.048	0.066
ϕ_2	0.053	0.038	0.035	0.081	0.041	0.072	0.052
ϕ_3	0.083	0.025	0.040	0.065	0.049	0.054	0.057
ϕ_4	0.056	0.023	0.051	0.088	0.063	0.068	0.026
ϕ_5	0.063	0.036	0.050	0.069	0.034	0.059	0.056
ϕ_6	0.090	0.028	0.034	0.081	0.074	0.041	0.019
ϕ_7	0.058	0.030	0.055	0.067	0.035	0.066	0.053

Table 8 The TOPSIS result and ranking of alternatives

C_n/A_n	S^+_i	S^-_i	p_i	Rank
ϕ_1	0.057	0.065	0.53	3
ϕ_2	0.050	0.058	0.54	2
ϕ_3	0.040	0.053	0.57	1
ϕ_4	0.060	0.049	0.44	6
ϕ_5	0.054	0.041	0.43	4
ϕ_6	0.069	0.070	0.50	5
ϕ_7	0.063	0.035	0.36	7

Step 5. Calculating the weights of DMs.

DMs’ judgments are collected by using the following equation:

$$r^{k}_{ij} = \frac{[T^+(x)_{nl}, I^+(x)_{nl}, F^+(x)_{nl}, T^-(x)_{nl}, \Gamma(x)_{nl}, F^-(x)_{nl}]}{n} \tag{5}$$

Then, the score value after aggregating the opinions of DMs for each criteria using Eq. (1) is calculated, and the obtaining weights are normalized.

Step 6. Construct the evaluation matrix.

Build the evaluation matrix $A_i \times C_j$ with the assistance of BNNs to evaluate the ratings of alternatives with respect to each criterion. DMs use the linguistic terms shown in subsection 3.2. Let R^{k}_{ij} be a (BN) decision matrix of the Kth DMs, then:

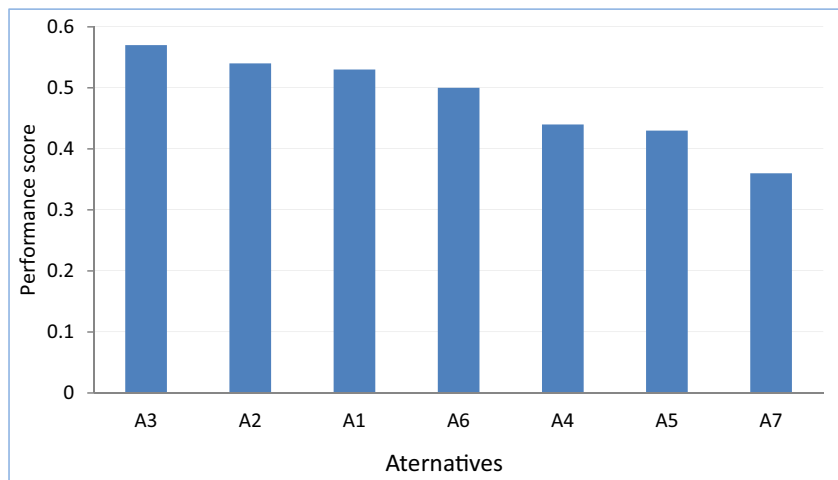
$$R^{k}_{ij} = \begin{bmatrix} r^{k}_{11} & \dots & r^{k}_{1n} \\ \vdots & \ddots & \vdots \\ r^{k}_{m1} & \dots & r^{k}_{mn} \end{bmatrix}, k \in K \tag{6}$$

where $r^{k}_{ij} = [T^+(x), I^+(x), F^+(x), T^-(x), \Gamma(x), F^-(x)]$, $k = 1, 2, \dots, K, i = 1, 2, \dots, m, j = 1, 2, \dots, n$.

Step 7. Calculate the crisp value of matrix.

Use the de-neutrosophication Eq. (1) for transforming bipolar neutrosophic numbers into crisp values for each factor

Fig. 6 The ranking of alternatives by the suggested method



r^k_{ij} and compare the score values according to Definition 2.1.1.5.

Step 8. Aggregate the final evaluation matrix.

Using Eq. (7), aggregate the crisp values of evaluation matrices into a final matrix.

$$\tilde{a}_{ij} = \frac{\tilde{a}_{ij}^1 + \dots + \tilde{a}_{ij}^n}{n} \tag{7}$$

$$A_w(\tilde{a}_1, \tilde{a}_2, \dots, \tilde{a}_n) = \sum_{j=1}^n \omega_j \tilde{a}_j \tag{10}$$

$$= \left(1 - \prod_{j=1}^n (1 - T_j^+) \right)^{\omega_j}, \prod_{j=1}^n T_j^{+\omega_j}, \prod_{j=1}^n F_j^{+\omega_j}, -\prod_{j=1}^n (-T_j^-)^{\omega_j}, -1 \left(\prod_{j=1}^n (1 - (-T_j^-)) \right)^{\omega_j}, - \left(1 - \prod_{j=1}^n (1 - (-F_j^-)) \right)^{\omega_j} \right)$$

Step 9. Define Ideal Solution A^+, A^- .

Calculate the positive and negative ideal solution using Eqs. (11, 12).

$$A^+ = \{ \langle \max(\delta_{ij} | i = 1, 2, \dots, m) | j \in J^+ \rangle, \langle \min(\delta_{ij} | i = 1, 2, \dots, m) | j \in J^- \rangle \} \tag{11}$$

$$A^- = \{ \langle \min(\delta_{ij} | i = 1, 2, \dots, m) | j \in J^+ \rangle, \langle \max(\delta_{ij} | i = 1, 2, \dots, m) | j \in J^- \rangle \} \tag{12}$$

Step 10. Positive and Negative Ideal Solution S^+_i, S^-_i .

Calculate the Euclidean distance between positive solution (S^+_i) and negative ideal solution (S^-_i) using Eqs. (13, 14).

$$S^+_i = \sqrt{\sum_{j=1}^n (\delta_{ij} - \delta_j^+)^2} \quad i = 1, 2, \dots, m, \tag{13}$$

Then, normalize the obtained matrix by Eq. (8).

$$H_{rt} = \frac{X_{rt}}{\sqrt{\sum_{i=1}^m X_{rt}^2}}; r = 1, 2, \dots, m; t = 1, 2, \dots, n. \tag{8}$$

After that, calculate the weight matrix by Eq. (9).

$$Q_{rt} = w_z \times H_{rt} \tag{9}$$

or using Eq. (10)

$$S^-_i = \sqrt{\sum_{j=1}^n (\delta_{ij} - \delta_j^-)^2} \quad i = 1, 2, \dots, m \tag{14}$$

Step 11. Rank the alternatives based on closeness coefficient.

$$P_i = \frac{S^-_i}{S^+_i + S^-_i} \quad i = 1, 2, \dots, m \tag{15}$$

Step 12. Comparing the obtained results with other methods.

Step 13. Check the stability of variations in rankings by Spearman coefficient of correlation.

Numerical Experiment

We introduced in this section a numerical case, which requires methods and data analysis to test the competence and

Table 9 The aggregated crisp values of decision matrix using by AHP method

C_n/A_n	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Φ_1	0.48	0.69	0.5	0.64	0.55	0.51	0.82
Φ_2	0.53	0.73	0.55	0.67	0.51	0.84	0.69
Φ_3	0.85	0.48	0.63	0.54	0.61	0.63	0.76
Φ_4	0.47	0.38	0.66	0.60	0.64	0.64	0.29
Φ_5	0.65	0.69	0.78	0.57	0.42	0.68	0.75
Φ_6	0.76	0.44	0.44	0.56	0.77	0.39	0.22
Φ_7	0.53	0.51	0.77	0.49	0.39	0.68	0.64

efficiency of suggested framework for selection of appropriate medical devices (MDs).

Case Study

Companies seek developing sugar analyzing devices for diabetics. Therefore, we introduce a practical case to select a sugar analyzing device. There are four decision makers; DM_1, DM_2, DM_3 and DM_4 , and seven alternatives $A_1, A_2, A_3, A_4, A_5, A_6$ and A_7 . For evaluating the SMDs alternatives, seven criteria are considered as selection factors: C_1 (Safety), C_2 (Cost), (Flexibility), C_4 (Quality), C_5 (Ease of use), C_6 (Maintenance Requirements) and C_7 (Service Life), as listed in Fig. 4.

The Calculation Process of the Neutrosophic with TOPSIS Technique

Step 1. Organize a committee of DMs and determine the goal, alternatives and valuation criteria.

A committee consisting of four DMs is constructed to select the best alternatives of sugar analyzing smart medical devices for diabetics, $A_i = \{A_1, A_2, A_3, A_4, A_5, A_6, A_7\}$, offered by different medical device producers . These alternatives are estimated based on seven criteria $c_j = \{c_1, c_2, c_3, c_4, c_5, c_6, c_7\}$, which are collected from comprehensive commentaries and DMs’ opinions.

Table 10 The ranking of alternatives under AHP method

Alternatives	V_i	Ranking
Φ_1	0.59	3
Φ_2	0.64	2
Φ_3	0.65	5
Φ_4	0.54	1
Φ_5	0.63	7
Φ_6	0.52	4
Φ_7	0.56	6

Table 11 The weighted matrix under MOORA method

C_n/A_n	C_1	C_2	C_3	C_4	C_5	C_6	C_7
Φ_1	0.051	0.039	0.034	0.084	0.048	0.048	0.066
Φ_2	0.053	0.038	0.035	0.081	0.041	0.072	0.052
Φ_3	0.083	0.025	0.040	0.065	0.049	0.054	0.057
Φ_4	0.056	0.023	0.051	0.088	0.063	0.068	0.026
Φ_5	0.063	0.036	0.050	0.069	0.034	0.059	0.056
Φ_6	0.090	0.028	0.034	0.081	0.074	0.041	0.019
Φ_7	0.058	0.030	0.055	0.067	0.035	0.066	0.053

Step 2, 3, 4. Determine the appropriate (LVs) linguistic variables for weights (W_n) of criteria (C_n) and alternatives (A_n) with regard to each criterion. Each linguistic variable is a bipolar neutrosophic number (BNN). For criteria weights and for compilation alternatives, the linguistic variables are as follows: Excessively Good (EG) = $\langle 0.9, 0.1, 0.0, 0.0, -0.8, -0.9 \rangle$; where the first three numbers present the positive membership degree $T^+(x)$, $I^+(x)$, $F^+(x)$ 0.9, 0.1 and 0.0 respectively, $T^+(x)$ the truth degree in positive membership, $I^+(x)$ the indeterminancy degree and finally $F^+(x)$ the falsity degree. The last three numbers present the negative membership degree $T^-(x)$, $I^-(x)$, $F^-(x)$ 0.0, -0.8 and -0.9 respectively, where $T^-(x)$ the truth degree in negative membership, $I^-(x)$ the indeterminancy degree and finally $F^-(x)$ the falsity degree. Very Good (VG) = $\langle 1.0, 0.0, 0.1, -0.3, -0.8, -0.9 \rangle$, Midst Good (MG) = $\langle 0.8, 0.5, 0.6, -0.1, -0.8, -0.9 \rangle$, Perfect (P) = $\langle 0.7, 0.6, 0.5, -0.2, -0.5, -0.6 \rangle$, Approximately Similar (AS) = $\langle 0.5, 0.2, 0.3, -0.3, -0.1, -0.3 \rangle$, Bad (B) = $\langle 0.4, 0.4, 0.3, -0.5, -0.2, -0.1 \rangle$, Midst Bad (MB) = $\langle 0.3, 0.1, 0.9, -0.4, -0.2, -0.1 \rangle$, Very Bad (VB) = $\langle 0.2, 0.3, 0.4, -0.8, -0.6, -0.4 \rangle$, Excessively Bad (EB) = $\langle 0.1, 0.9, 0.8, -0.9, -0.2, -0.1 \rangle$.

Step 5. Calculating the weights of DMs

The prior (LVs) linguistic variables are used by experts and (DMs) decision makers to clarify their priorities, preferences and the confirmation degree of linguistic variable according to

Table 12 The ranking of alternatives under MOORA method

Alternatives	P^*_i	Ranking
Φ_1	1.44	3
Φ_2	1.83	1
Φ_3	1.39	2
Φ_4	2.35	7
Φ_5	2.22	5
Φ_6	2.76	4
Φ_7	2.17	6

Table 13 The ranking of alternatives by methods

Alternatives	Pros. Method (1)	AHP (2)	MOORA(3)
Φ_1	3	3	3
Φ_2	2	2	1
Φ_3	1	5	2
Φ_4	6	1	7
Φ_5	4	7	5
Φ_6	5	4	4
Φ_7	7	6	6

each (DM) decision maker or expert. The Table 1 presents the criteria weights according to all decision makers, after deciding (LVs) linguistic variables to each decision maker or expert.

Convert the linguistic variables into bipolar neutrosophic numbers as in Table 2. Use Eq. (5) to aggregate weights in BNNs. Then, employ Eq. (1) to calculate the crisp weight values. After that, make a normalization procedure on the previous values, as in Table 3. The Fig. 5 shows the values of weights that equals: $w_1 = 0.17, w_2 = 0.09, w_3 = 0.11, w_4 = 0.21, w_5 = 0.14, w_6 = 0.15, w_7 = 0.13$.

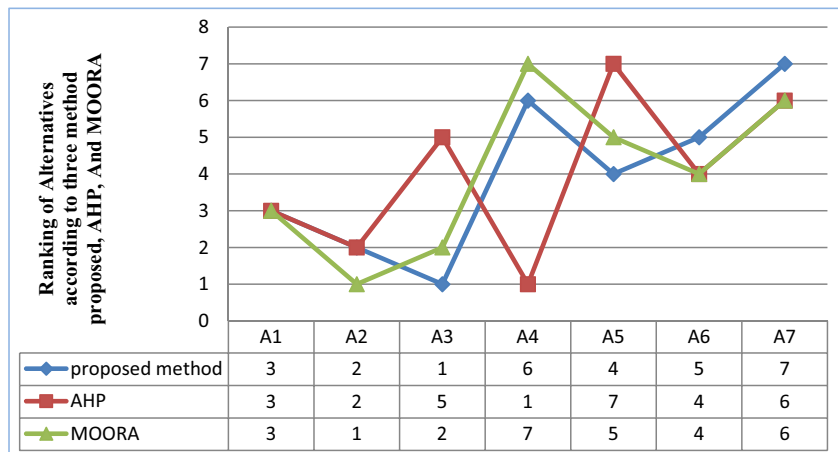
Step 6. Construct the evaluation matrix.

Obtain the final decision matrix by making the aggregation procedure of decision makers' priorities and preferences, as in Table 4.

Step 7, 8. Calculate the crisp values of matrices and insert them into the aggregated matrix.

Let each decision maker construct the matrix by comparing the five alternatives against each criterion, by utilizing the bipolar neutrosophic scale, previously presented in Step 2 of this section. Use Eq. (1) to progress towards de-neutrosophication in order to transform the bipolar neutrosophic numbers into their crisp forms. Then, aggregate the matrices and get the last evaluation matrix, pertinent to decision makers' committee. Employ Eq. (7) to aggregate

Fig. 7 The ranking of alternatives according to the three methods: our method, AHP and MOORA



crisp values of evaluation matrices into a final matrix, as in Table 5.

Apply the normalization process by using Eq. (8) to obtain the normalized evaluation matrix, as presented in Table 6.

Build the weighted matrix by multiplying the normalized evaluation matrix by the weights of criteria using Eq. (9), as in Table 7.

Step 9. Define Ideal Solution A^+, A^- .

Define the ideal solutions using Eqs. (11) and (12) as follows:

$$A^+ = \{0.090, 0.039, 0.055, 0.088, 0.074, 0.072 \text{ and } 0.066\},$$

$$A^- = \{0.051, 0.023, 0.034, 0.065, 0.034, 0.041 \text{ and } 0.019\}.$$

Step 10. Positive and Negative Ideal Solution S^+, S^- .

Calculate the Euclidean distance between positive solution (S^+_i) and negative ideal solution (S^-_i) using Eqs. (13) and (14) as follows:

$$S^+_1 = \{0.057\}, S^+_2 = \{0.050\}, S^+_3 = \{0.040\}, S^+_4 = \{0.060\}, S^+_5 = \{0.054\}, S^+_6 = \{0.069\}, S^+_7 = \{0.063\}.$$

$$S^-_1 = \{0.065\}, S^-_2 = \{0.058\}, S^-_3 = \{0.053\}, S^-_4 = \{0.049\}, S^-_5 = \{0.041\}, S^-_6 = \{0.070\}, S^-_7 = \{0.035\}.$$

Step 11. Rank the alternatives based on closeness coefficient.

Calculate the performance score using Eq. (15), and make the last ranking of alternatives as presented in Table 8.

The order for the optimal alternatives of smart medical devices is Alternative 3, Alternative 2, Alternative 1, Alternative 6, Alternative 4, Alternative 5 and Alternative 7, as drawn in Fig. 6.

Table 14 The correlation coefficient between the proposed model and other methods

Correlate (1, 2)	Correlate (1, 3)
0.071	0.893

Step 12. Comparing the obtained results with other methods.

In this step, compare the results of suggested method with the results obtained by other existing methods, such as analytic hierarchy process (AHP) or a method from multi objective decision-making techniques, as MOORA, to validate our model. It is known that AHP does not consider feedback and interdependency among elements of problem. The comparison matrix of alternatives relevant to each sub-criterion is presented in Table 9. The final ranking of alternatives by AHP method is listed in Table 10.

In addition, we used MOORA technique to validate our proposed approach that is the multi objective decision making (MODM) techniques submitted by Esra and Işık [33]. The equations that are applied in our computation of MOORA method are founded in [13]. The MOORA normalized matrix and ranking of alternatives are listed in Tables 11 and 12.

The proposed method and the other two methods used for the ranking of alternatives are aggregated in Table 13 and presented in Fig. 7. We used SPSS program to calculate the correlation coefficient among the different techniques and the proposed approach, as shown in Table 14.

It is clear that alternative 3 is the best alternative according to the results of the three methods applied, including the proposed method.

Concluding Remarks

Better health attention can be possible by tracking medical requirements of patients. Nowadays, patients tend to measure themselves their activity, and consequently the medical devices are not solely designed for healthcare specialists. Medical tools, such as cardiac monitors or sugar analysis, are getting smarter and started to be incorporated into numerous devices, e.g. smart watches or smartphones. This research introduces the Neutrosophic TOPSIS for an MCDM problem method, namely the selection of sugar analyzing device for diabetics. Furthermore, the suggested method is applied to a practical case to compare seven smart medical devices using seven evaluation criteria to validate the suggested approach, employing experts' opinion and extensive literature review. The suggested method produces more realistic and accurate results than other MCDM techniques, because TOPSIS can capture, implement and model interactions between selection

criteria. In addition, a collection of experts is often more beneficial than a single one, in order to reduce partiality and bias of individual opinions and judgments, and the use of Neutrosophic values enhances the transaction of selection. The Neutrosophic theory can help in preventing the loss of data, present linguistic declarations into analytical models and help in including of nonnumeric statements. To complete the ranking of alternatives based on the information collected, we employ the neutrosophic with TOPSIS method. The verification and effectiveness of the suggested method are compared with other methods. Eventually, the Spearman's coefficient of correlation is applied to determine the relation among the results obtained by comparison. Although the presented methodology is used for the selection of sugar analyzing devices for diabetics' patients, it can also be applied for other SMD valuations. Additional research could extend the suggested methodology to other types of SMDs selection procedures.

Compliance with Ethical Standards

Conflict of Interest The authors declared that we do not have any conflict of interest for this research work. This article does not contain any studies with human participants or animals performed by any of the authors.

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