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# Multi-Attribute Decision-Making Based on Preference Perspective with Interval Neutrosophic Sets in Venture Capital

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**Abstract:** Fuzzy information in venture capital can be well expressed by neutrosophic numbers, and TODIM method is an effective tool for multi-attribute decision-making. The distance measure is an essential step in TODIM method. The keystone of this paper is to define several new distance measures, in particular the improved interval neutrosophic Euclidean distance, and these measures are applied in the TODIM method for multi-attribute decision-making. Firstly, the normalized generalized interval neutrosophic Hausdorff distance is defined and proved to be valid in this paper. Secondly, we define a weighted parameter interval neutrosophic distance and discuss whether different weight parameters affect the decision result based on TODIM method. Thirdly, considering the preference perspective of decision-makers in behavioral economics, we define the improved interval neutrosophic Euclidean distance with the known parameter of risk preference. Finally, an application example is given to compare the effects of different parameters on the result and discuss the feasibility of these two distance measures in TODIM method.

**Keywords:** Interval Neutrosophic Sets; distance measure; venture capital; TODIM method; multi-attribute decision-making

## 1. Introduction

It is well known that the attribute decision information in multi-attribute investment is uncertain, incomplete, and inconsistent. This kind of information is often called fuzzy information. Therefore, to describe fuzzy information in real life better. Zadeh [1] first proposed the concept of fuzzy number and fuzzy set (FS). Then interval-valued FS (IVFS) [2], hesitant FS (HFS) [3], complex FS (CFS) [4], and hesitant fuzzy linguistic set (HFLS) [5] were developed based on FS and were also used to solve some decision problems. For instance, Krohling and Souza [6] proposed a hybrid approach combining prospect theory and FS to handle risk and uncertainty in multi-criteria decision-making (MCDM) problems. Fan et al. [7] proposed an extended TODIM method to solve the hybrid multiple-attribute decision-making (MADM) problem in which attribute values are represented in FS. Wang et al. [8] introduced the risk psychological factors of the decision maker into the TOPSIS method to making MADM in the form of HFS. Xu et al. [9] defined novel correlation coefficients between HFS and applied them in MADM problems. Tang et al. [10] developed some novel distance measures and similarity measures for HFS to solving MADM problem. In addition, for handling MCDM problems with linguistic hesitant fuzzy information, Zhou et al. [11] discussed the distance measure based on

TOPSIS, VIKOR (Vlse Kriterijums ka Optimizacija I Kompromisno Resenje) and TODIM methods, and Tao et al. [12] developed a new version of distance measure for pattern recognition, fuzzy clustering, and MADM. Although these fuzzy numbers have been applied, it can only consider the membership degree and ignore the existence of non-membership degree. The range of application is narrow, and it needs new ways and further development.

Based on this, some scholars proposed intuitionistic fuzzy set (IFS) [13], interval-valued IFS [14], complex IFS [15], and intuitionistic hesitant fuzzy set (IHFS) [16] and applied them to more practical problems recently. Xia and Xu [17] developed the hesitant fuzzy aggregation operators based on the interconnection between HFS and IFS for MADM. Wang and Jia [18] proposed an investment decision-making method based on newly defined expectation of intuitionistic trapezoidal fuzzy numbers. A MADM method based on the Zhenyuan integral of IFS was presented by Zeng and Mu [19]. Yun et al. [20] presented new definitions on distance and similarity measures between IFS by combining them with hesitation degree to deal with pattern recognition problems. Moreover, Yin et al. [21] proposed an interval-valued intuitionistic fuzzy MADM method based on the improved fuzzy entropy. Tan et al. [22] introduced an extended TOPSIS method based on new distance measures under IHF environment. These sets supplement the non-membership degree to the FS, which can solve the incomplete information in decision-making, but cannot deal with the uncertain and inconsistent information.

To deal with fuzzy information more comprehensively, Smarandache [23] proposed the neutrosophic set(NS) theory. This theory points out that NS is the set whose truth-membership function, indeterminacy-membership function and falsity-membership function are nonstandard unit intervals. For simplifying NS and applying it to real life, Wang et al. [24] defined single-valued NS (SVNS) and put forward the corresponding decision-making method on this basis. Considering that SVNS may not be able to accurately describe the truth-membership, indeterminacy-membership and falsity-membership of things in real life, Wang [25] further defined interval NS (INS). After that, although it also defined simplified NS [26], multi-valued NS [27], quadripartitioned SVNS [28], complex NS [29] and others, INS can describe the MADM information and evaluate the impact of each attribute on the decision-making results through some corresponding methods very well. These methods include TODIM [7,30–33], TOPSIS [22,34–38], VIKOR [39], EDAS(Evaluation Based on Distance from Average Solution) [40], PROMETHEE [41], ELECTRE [42] and so on. For example, Ye [43] proposed similarity measures between INSs based on the Hamming and Euclidean distance, and developed a MCDM method based on the similarity degree. Majumdar [44] defined a special hybrid neutrosophic set for decision-making. Liu and Zhang [45] presented the distance measurement between multi-valued neutrosophic sets (MVNSs) and applied the VIKOR method to address MCDM problems and defined the comparison method. Liu and Luo [46] defined the single-valued neutrosophic ideal solution (SVNIS) and the weighted distance measure for dealing with decision-making problems. Huang [47] demonstrated the effectiveness of the proposed clustering method and MCDM method based on a new distance (similarity) measure between SVNSs. Applying a special subset hood measure with the proposed Hausdorff distance, Ji and Zhang [48] put forward a method for MCDM problems under interval neutrosophic environments. Liu et al. [49] combined the INS with the cloud model and proposed an extended TOPSIS method for multi-attribute group decision-making (MAGDM) problems with unknown attribute weights. Nancy and Garg presented an improved score function of SVNNs [50] and the SVN entropy measure of order $\alpha$ to solve the decision-making problem [51]. Besides, they also proposed some new biparametric distance measures on SVNSs with applications to pattern recognition and medical diagnosis [52] and presented TOPSIS method under an interval NS environment to solve decision-making problems [38]. Ji et al. [33] proposed a projection-based TODIM method under multi-valued neutrosophic environments. Zhang and Liu [32] combined TODIM and NS to give a new method to handle MAGDM problems. Peng and Dai [53] initiated MABAC, TOPSIS and similarity measure for MADM problems based on a new score function and a new axiomatic definition distance measure of SVNS. Rıdvan and Gökçe [54] developed a simplified neutrosophic ordered weighted distance operator to solve MAGDM problems. As mentioned above, numerous methods are applicable in different decision-making situations; however, advice for selecting the most appropriate for the specific field of application and problem has not been thoroughly investigated [55]. However, according to this previous research, it can be seen that TODIM is one of the commonly used methods for MADM problems under interval neutrosophic environments.

The classical TODIM method is proposed by Gomes and Lima [56] based on prospect theory. It is a typical MADM method considering the psychological behavior of decision-makers. The main idea is to establish the relative dominance function of any scheme with respect to other schemes based on the value function of the prospect theory, and then rank the schemes according to the obtained dominance. Based on observation, the selection of distance formula is a crucial step in TODIM method and several classical distance formulas are usually used, such as Hamming distance, Euclidean distance and Hausdorff distance. Ye [43] first defined the Hamming distance, Euclidean distance and their normalized forms of INS. Broumi and Smarandache [57] introduced the normalized generalized interval neutrosophic distance. Ye and Du [58] proposed the Hausdorff distance of INS.

In venture capital, different venture capitalists have different attitudes towards risk. Some people may like the stimulus of big gains and losses, while others may be willing to pursue steady returns. So we must consider the risk preference of venture capitalists when we make decisions. Considering the influence of distance formula on decision-making results, this paper first defines the normalized generalized interval neutrosophic Hausdorff distance and the normalized generalized parameter distance with normalized generalized interval neutrosophic distance, and then discusses the influence of parameters on decision-making results. Then, considering the preference psychology of decision-makers in venture capital, a new Euclidean distance is defined based on preference perspective and the conclusions of the previous part. Finally, an example is used to verify its rationality and feasibility.

## 2. Problem Description

When investing in a project, different investors have different expectations for the attributes of project risk and project return. Some people may like the stimulus of big gains and losses, while others may be willing to pursue steady returns. So, the attitudes can be divided into risk averters, risk lovers, and risk neutrals according to the investors' preferences for risk. Risk averters prefer assets with low risk when the expected return is the same as the other two, and they prefer assets with higher expected return while for assets with the same risk as the other two. Contrary to the risk averters, risk lovers usually take the initiative to pursue risk, preferring volatility to stability and their principle of choosing assets is that when the expected return is the same as the other two, they choose the riskier option because it will bring them greater utility. In contrast to the former two, risk neutrals usually do not avoid risk or pursue risk and, regardless of risk, their criteria for choosing assets is the profit of expected returns. Therefore, different psychological and behavioral preferences of decision-makers are one of the key factors affecting decision-making results. A venture capitalist (VC) wants to choose the best enterprise (EN) from a lot of alternatives to invest; thus, a VC will analyze different attributes of different ENs and make the best decision by prioritizing these alternatives based on known theory.

The feature of venture capital roughly meets the following conditions:

(1) The enterprises are generally small- and medium-sized, in the early stage of their business, and most of them are high-technology enterprises;
(2) The term of investment for the VC firm is at least 3–5 years, and the way of investment is equity investment. In general, these shares account for about 30% of the shares of an enterprise. However, the investors have no controlling rights and the enterprises need not give investors anything as collateral or mortgage;
(3) Investment must be highly specialized and procedural;
(4) Normally, investors will take an active part in the operation and management of enterprises and provide value-added services;

(5) As the aim of investment is to achieve value-added purposes and pursue excess returns, the investors will withdraw capital through listing, merger and acquisition, or other forms of equity transfer.

There is something important we mentioned before—the attributes we choose.
For example, several important attributes are listed here:

(1) Team management. Investing in team of the company is better than investing in the project, especially investing in the leader of this team. A good leader is the guarantee of success;
(2) Outlook of Industry. The industry with potential for future growth is the best choice for the VC firms;
(3) Enterprise competitiveness. Enterprises with core competitiveness can surpass other competitors in the same industry;
(4) Good mode: business mode + profit mode + marketing mode;
(5) High business income and high proportion of operating profit;
(6) Clear structure: equity structure + top management structure + business structure + customer structure + supplier structure.

## 3. Interval Neutrosophic Sets

This section reviews NS and some basic formula of INS.

### 3.1. NS

**Definition 1.** *Let X be a space of points(objects), with a generic element in X denoted by x. A NS A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$, and a falsity-membership function $F_A(x)$. The function $T_A(x)$,$I_A(x)$,$F_A(x)$ are real standard or nonstandard subsets of $]0^-, 1^+[$. That is $T_{A(x)}$: $X \to ]0^-, 1^+[$, $I_{A(x)}$:$X \to ]0^-, 1^+[$, $F_{A(x)}$:$X \to ]0^-, 1^+[$.*

*A NS can be expressed by $A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle | x \in X\}$ with the condition of $0^- \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.*

**Definition 2.** *The complement of a NS A is denoted by $A^C$ and is defined as $T_{A^C}(x)$=$1^+ \ominus T_A(x)$, $I_{A^C}(x)$=$1^+ \ominus I_A(x)$, $F_{A^C}(x)$=$1^+ \ominus F_A(x)$ for every x in X.*

**Definition 3.** *A NS A is contained in the other NS B, $A \subseteq B$ if and only if $\inf T_A(x) \leq \inf T_B(x)$, $\sup T_A(x) \leq \sup T_B(x)$, $\inf I_A(x) \geq \inf I_B(x)$, $\sup I_A(x) \geq \sup I_B(x)$, $\inf F_A(x) \geq \inf F_B(x)$, $\sup F_A(x) \geq \sup F_B(x)$ for every x in X.*

### 3.2. INS

**Definition 4.** *Let X be a space of points(objects) with generic elements in X denoted by x. An INS A in X is characterized by a truth-membership function $T_A(x)$, an indeterminacy-membership function $I_A(x)$, and a falsity-membership function $F_A(x)$.*

*For each point x in X, we have that $T_A(x)$=$[\inf T_A(x), \sup T_A(x)]$, $I_A(x)$=$[\inf I_A(x), \sup I_A(x)]$, $F_A(x)$=$[\inf F_A(x), \sup F_A(x)] \subseteq [0, 1]$, and with the condition of $0 \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3$.*

*For convenience, it can be expressed as $A = \langle [T^L, T^U], [I^L, I^U], [F^L, F^U]\rangle$.*

**Definition 5.** *The complement of an INS A is denoted by $A^C$ and is defined as $A^C = \langle F_A(x), [(1 - \sup I_A(x)), (1 - \inf I_A(x))], T_A(x)\rangle$.*

*For convenience, it can be expressed to be $A^C = \langle [F^L, F^U], [(1 - I^U), (1 - I^L)], [T^L, T^U]\rangle$.*

**Definition 6.** *The expectation of an INS A is*

$$E(A) = \frac{1}{6}(T^L + T^U + 1) + (I^L + I^U + 1) - (F^L + F^U). \tag{1}$$

## 4. TODIM Method for INS MADM in Venture Capital

We proposed that here is a MADM problem. Let $A = (A_1, A_2, \ldots, A_m)$ be the alternatives, and $G = (G_1, G_2, \ldots, G_n)$ be the attributes, and $w = (w_1, w_2, \ldots, w_n)$ be the weight of $G_j (j = 1, 2, \ldots, n)$, where $0 \le w_j \le 1$, and $\sum_{j=1}^{n} w_j = 1$. Here, the weight coefficient $w_j (j = 1, 2, \ldots, n)$ is determined by decision-makers. Assume that the interval neutrosophic number $a_{ij}$ is given for alternative $A_i$ under $G_j (i = 1, 2, \ldots, m, j = 1, 2, \ldots, n)$. Then let $A = (a_{ij})_{m \times n}$ be a decision matric.

The following shows the complete for the method.

Step 1: Standardize the decision information to get the normalized decision matric. That is, normalizing $A = (a_{ij})_{m \times n}$ into $B = (b_{ij})_{m \times n}$. If the decision is an efficient factor, it cannot be changed; if the decision is a cost factor, the decision should be changed by its complementary set;

Step 2: The corresponding weight $w_j (j = 1, 2, \ldots, n)$ is given here;

Step 3: Choose $w_r = max\{w_j | i = 1, 2, \ldots, n\}$ to be the criterion, and $w_{jr} = \frac{w_j}{w_r} (j, r = 1, 2, \ldots, n)$ is relative weight of $G_j$ to $G_r$;

Step 4: Figure out the dominance degree of $B_i$ over every alternative $B_t$:

$$\delta(B_i, B_t) = \sum_{j=1}^{n} \varphi_j(B_i, B_t) (i = 1, 2, ..., m) \tag{2}$$

where

$$\varphi_j(B_i, B_t) = \begin{cases} \sqrt{\frac{w_{jr} d(b_{ij} - b_{tj})}{\sum_{j=1}^{n} w_{jr}}} & , E(b_{ij}) - E(b_{tj}) > 0 \\ 0 & , E(b_{ij}) - E(b_{tj}) = 0 \\ -\frac{1}{\theta} \sqrt{\frac{(\sum_{j=1}^{n} w_{jr}) d(b_{tj} - b_{ij})}{w_{jr}}} & , E(b_{ij}) - E(b_{tj}) < 0 \end{cases}. \tag{3}$$

where $d(b_{ij}, b_{tj})$ denotes the distance between $b_i$ and $b_t$ under $G_j$, and $E(b_{ij})$ is the expectation of $b_i$ under $G_j$.

In this function, $\varphi_j(B_i, B_t)$ represents the dominance degree of $B_i$ over every alternative $B_t$ under attribute $G_j$; the parameter $\theta$ is the attenuation factor of the losses. If $E(b_{ij}) - E(b_{tj}) > 0$ , $\varphi_j(B_i, B_t)$ shows a gain; if $E(b_{ij}) - E(b_{tj}) < 0$ , $\varphi_j(B_i, B_t)$ expresses a loss;

Step 5: Work out the overall dominance of $B_i$ by following function

$$\xi_i = \frac{\sum_{t=1}^{m} \delta(B_i, B_t) - \min\limits_{1 \le i \le m} \{\sum_{t=1}^{m} \delta(B_i, B_t)\}}{\max\limits_{1 \le i \le m} \{\sum_{t=1}^{m} \delta(B_i, B_t)\} - \min\limits_{1 \le i \le m} \{\sum_{t=1}^{m} \delta(B_i, B_t)\}}; \tag{4}$$

Step 6: Ranking all alternatives according to the value of $\xi_i$. The larger the value of $\xi_i$, the better the alternative is.

## 5. Existing Distance Measures

Let $A = \langle [T_A^L, T_A^U], [I_A^L, I_A^U], [F_A^L, F_A^U] \rangle$ and $B = \langle [T_B^L, T_B^U], [I_B^L, I_B^U], [F_B^L, F_B^U] \rangle$ be two INSs.

**Definition 7.** *The normalized interval neutrosophic Hamming distance [43] is*

$$D_{Hm}(A, B) = \frac{1}{6} \{ |T_A^L - T_B^L| + |T_A^U - T_B^U| + |I_A^L - I_B^L| + |I_A^U - I_B^U| + |F_A^L - F_B^L| + |F_A^U - F_B^U| \}. \tag{5}$$

**Definition 8.** *The normalized interval neutrosophic Euclidean distance [43] is*

$$D_E(A,B) = \frac{1}{6}\{|T_A^L - T_B^L|^2 + |T_A^U - T_B^U|^2 + |I_A^L - I_B^L|^2 + |I_A^U - I_B^U|^2 + |F_A^L - F_B^L|^2 + |F_A^U - F_B^U|^2\}^{\frac{1}{2}}. \quad (6)$$

**Definition 9.** *The normalized generalized interval neutrosophic distance [57] is*

$$D_g(A,B) = \frac{1}{6}\{|T_A^L - T_B^L|^\lambda + |T_A^U - T_B^U|^\lambda + |I_A^L - I_B^L|^\lambda + |I_A^U - I_B^U|^\lambda + |F_A^L - F_B^L|^\lambda + |F_A^U - F_B^U|^\lambda\}^{\frac{1}{\lambda}}, \quad (7)$$

*with the condition of* $\lambda > 0$*. When* $\lambda = 1$*, it is the Hamming distance; when* $\lambda = 2$*, it is the Euclidean distance.*

**Definition 10.** *The normalized interval neutrosophic Hausdorff distance [58] is*

$$D_{Hd} = \max\{\frac{1}{2}(|T_A^L - T_B^L| + |T_A^U - T_B^U|), \frac{1}{2}(|I_A^L - I_B^L| + |I_A^U - I_B^U|), \frac{1}{2}(|F_A^L - F_B^L| + |F_A^U - F_B^U|)\}. \quad (8)$$

## 6. Improved Distance Measures

### 6.1. The Weighted Parameter Interval Neutrosophic Distance

In this section, we first present the definition of the normalized generalized interval neutrosophic Hausdorff distance between two INSs $A$ and $B$.

**Definition 11.** *The normalized generalized interval neutrosophic Hausdorff distance is*

$$\begin{aligned} D_{gHd}(A,B) = \max\{&\frac{1}{2}(|T_A^L - T_B^L|^\mu + |T_A^U - T_B^U|^\mu)^{\frac{1}{\mu}}, \frac{1}{2}(|I_A^L - I_B^L|^\mu + |I_A^U - I_B^U|^\mu)^{\frac{1}{\mu}}, \\ &\frac{1}{2}(|F_A^L - F_B^L|^\mu + |F_A^U - F_B^U|^\mu)^{\frac{1}{\mu}}\} \end{aligned} \quad (9)$$

$\mu > 0$*, when* $\mu = 1$*, it is the Hausdorff distance.*

**Proposition 1.** *The above defined the normalized generalized interval neutrosophic Hausdorff distance* $D_{gHd}(A,B)$ *between INSs A and B satisfies the following properties (1)–(4):*

*(1)* $D_{gHd}(A,B) \geq 0$*;*

*(2)* $D_{gHd}(A,B) = 0$ *if and only if* $A = B$*;*

*(3)* $D_{gHd}(A,B) = D_{gHd}(B,A)$*;*

*(4) If* $A \subseteq B \subseteq C$*, C is the other INS in X, then* $D_{gHd}(A,C) \geq D_{gHd}(A,B)$ *and* $D_{gHd}(A,C) \geq D_{gHd}(B,C)$*.*

It can be proved that the theorem is valid, and the proof process is omitted.

Then, considering the influence of the parameter of (7) and (9), we introduce the weight parameter and define a novel interval neutrosophic distance between two INSs $A$ and $B$.

**Definition 12.** *The weighted parameter interval neutrosophic distance is*

$$\begin{aligned} &D_{wp} = \nu D_g + (1-\nu)D_{gHd} \\ &= \tfrac{\nu}{6}\{|T_A^L - T_B^L|^\lambda + |T_A^U - T_B^U|^\lambda + |I_A^L - I_B^L|^\lambda + |I_A^U - I_B^U|^\lambda + |F_A^L - F_B^L|^\lambda + |F_A^U - F_B^U|^\lambda\}^{\frac{1}{\lambda}} \\ &+(1-\nu)\max\{\tfrac{1}{2}(|T_A^L - T_B^L|^\mu + |T_A^U - T_B^U|^\mu)^{\frac{1}{\mu}}, \tfrac{1}{2}(|I_A^L - I_B^L|^\mu + |I_A^U - I_B^U|^\mu)^{\frac{1}{\mu}}, \tfrac{1}{2}(|F_A^L - F_B^L|^\mu + |F_A^U - F_B^U|^\mu)^{\frac{1}{\mu}}\}, \end{aligned} \quad (10)$$

*where* $\lambda > 0$*,* $\mu > 0$ *and* $1 \geq \nu \geq 0$*.*

*It can be proved that this theorem is established, and the proof process is omitted.*

Application and Analysis 1

In this paper, let us consider the decision-making problem adapted from Section 2 and assume that a VC firm wants to choose an innovating enterprise to invest to get maximum profit. So there are three enterprises as candidates, where $A = (A_1, A_2, A_3, A_4)$, and three attributes $G = (G_1, G_2, G_3)$. Assume that $a_{ij}$ is given for the alternative $A_i$ under the attribute $G_j$, $i = 1,2,3,4$ and $j = 1,2,3$. The first attribute is cost factor, and the decision should be changed by its complementary set; the next two are efficient factors, which should not be changed. The weight of the attribute is given by $w = (0.35, 0.25, 0.40)$, and the attenuation factor of the losses $\theta = -1$. For convenience of comparison, the decision information in [43] are used as a reference, the decision matric is

$$A = \begin{bmatrix} \langle[0.4,0.5][0.2,0.3][0.3,0.4]\rangle & \langle[0.4,0.6][0.1,0.3][0.2,0.4]\rangle & \langle[0.7,0.9][0.2,0.3][0.4,0.5]\rangle \\ \langle[0.6,0.7][0.1,0.2][0.2,0.3]\rangle & \langle[0.6,0.7][0.1,0.2][0.2,0.3]\rangle & \langle[0.3,0.6][0.3,0.5][0.8,0.9]\rangle \\ \langle[0.3,0.6][0.2,0.3][0.3,0.4]\rangle & \langle[0.5,0.6][0.2,0.3][0.3,0.4]\rangle & \langle[0.4,0.5][0.2,0.4][0.7,0.9]\rangle \\ \langle[0.7,0.8][0.0,0.1][0.1,0.2]\rangle & \langle[0.6,0.7][0.1,0.2][0.1,0.3]\rangle & \langle[0.6,0.7][0.3,0.4][0.8,0.9]\rangle \end{bmatrix}.$$

Then obtained the normalized decision matric

$$B = \begin{bmatrix} \langle[0.4,0.5][0.2,0.3][0.3,0.4]\rangle & \langle[0.4,0.6][0.1,0.3][0.2,0.4]\rangle & \langle[0.4,0.5][0.7,0.8][0.7,0.9]\rangle \\ \langle[0.6,0.7][0.1,0.2][0.2,0.3]\rangle & \langle[0.6,0.7][0.1,0.2][0.2,0.3]\rangle & \langle[0.8,0.9][0.5,0.7][0.3,0.6]\rangle \\ \langle[0.3,0.6][0.2,0.3][0.3,0.4]\rangle & \langle[0.5,0.6][0.2,0.3][0.3,0.4]\rangle & \langle[0.7,0.9][0.6,0.8][0.4,0.5]\rangle \\ \langle[0.7,0.8][0.0,0.1][0.1,0.2]\rangle & \langle[0.6,0.7][0.1,0.2][0.1,0.3]\rangle & \langle[0.8,0.9][0.6,0.7][0.6,0.7]\rangle \end{bmatrix}.$$

Then, we use the TODIM method and the weighted parameter interval neutrosophic distance for decision-making, and then discuss whether different weight parameters $\lambda$, $\mu$, and $\nu$ affect the decision result. For convenience, $A_i$ denotes the overall dominance and $FC$ denotes the final choice of VC.

(i) $\lambda$ changes while $\mu$ and $\nu$ remain unchanged, the ranking order is shown in Table 1.

**Table 1.** $\lambda$ changes.

| $\lambda$ | $\mu$ | $\nu$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | Ranking Order | FC |
|---|---|---|---|---|---|---|---|---|
| 1 | \ | 1 | 0 | 0.918 | 0.593 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 2 | \ | 1 | 0 | 0.929 | 0.629 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 3 | \ | 1 | 0 | 0.937 | 0.638 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 4 | \ | 1 | 0 | 0.943 | 0.640 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(ii) $\mu$ changes while $\lambda$ and $\nu$ remain unchanged, the ranking order is shown in Table 2.

**Table 2.** $\mu$ changes.

| $\lambda$ | $\mu$ | $\nu$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | Ranking Order | FC |
|---|---|---|---|---|---|---|---|---|
| \ | 1 | 0 | 0 | 0.964 | 0.648 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| \ | 2 | 0 | 0 | 0.955 | 0.611 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| \ | 3 | 0 | 0 | 0.955 | 0.591 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| \ | 4 | 0 | 0 | 0.955 | 0.583 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(iii) $\nu$ changes while $\lambda$ and $\mu$ remain unchanged, the ranking order is shown in Table 3.

**Table 3.** $\nu$ changes.

| $\lambda$ | $\mu$ | $\nu$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | Ranking Order | FC |
|---|---|---|---|---|---|---|---|---|
| 1 | 1 | 0.1 | 0 | 0.960 | 0.644 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 1 | 1 | 0.3 | 0 | 0.953 | 0.635 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 1 | 1 | 0.6 | 0 | 0.940 | 0.620 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 1 | 1 | 0.9 | 0 | 0.924 | 0.601 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

As shown in Tables 1–3, the ranking order is $A_4$, $A_2$, $A_3$, $A_1$ and $A_4$ is the best choice. This result is the same as that in [43]. Obviously, we can see that the change of $\lambda$, $\mu$, and $\nu$ has no effect on the decision results but it can affect the overall dominance value of alternative. Perhaps because of the insufficient number of attribute indicators and candidate enterprises discussed in this paper, there are some shortcomings in the results, which can be discussed in future research. In the discussion of this section, we have concluded that whatever the value of $\lambda$, $\mu$, and $\nu$, the decision result will not change, and we only discuss one distance measure in TODIM method to make decision in this paper.

### *6.2. The Improved Interval Neutrosophic Euclidean Distance*

The above measures (5), (6), and (8) have been widely used; however, they also have some drawbacks, which are illustrated with the numerical example that follows.

**Example 1.** *Consider two known candidates A and B, which are represented by INSs in a universe X given by* $A = \langle[0.4, 0.5][0.2, 0.3][0.3, 0.4]\rangle$ *and* $B = \langle[0.3, 0.4][0.1, 0.2][0.3, 0.4]\rangle$*, and another ideal pattern* $C = \langle[0.4, 0.5][0.1, 0.2][0.3, 0.4]\rangle$.

*We can choose A or B according to the* $D_{AC}$ *and* $D_{BC}$*, where D is defined in Equations (5), (6) and (8), and obtain their corresponding values as Table 4 shows:*

**Table 4.** Compare.

| | Equation (5) | Equation (6) | Equation (8) |
|---|---|---|---|
| $D_{AC}$ | 0.033 | 0.024 | 0.1 |
| $D_{BC}$ | 0.033 | 0.024 | 0.1 |

It seems to be worthless to calculate distance using the measures mentioned above. Thus, there is a need to build up a new distance measure that overcomes the shortcomings of the existing measures.

The risk preference of decision maker has important influence on risk management decision and attitude of different people towards risk is different. Therefore, different psychological and behavioral preferences of decision-makers are one of the key factors affecting decision-making results. This following improved distance sufficiently considered risk preference of the decision maker.

**Definition 13.** *The improved interval neutrosophic Euclidean distance with the known parameter of risk preference is*

$$D_I = \frac{1}{6}\{\rho_1(|T_A^L - T_B^L|^2 + |T_A^U - T_B^U|^2) + \rho_2(|I_A^L - I_B^L|^2 + |I_A^U - I_B^U|^2) + \rho_3(|F_A^L - F_B^L|^2 + |F_A^U - F_B^U|^2)\}^{\frac{1}{2}} \quad (11)$$

*If the decision maker is a strict risk averter,* $\rho_1 > \rho_2 > \rho_3$*;*
*if the decision maker is a middle risk averter,* $\rho_1 = \rho_2 > \rho_3$*;*
*if the decision maker is a primary risk averter,* $\rho_1 > \rho_2 = \rho_3$*;*
*if the decision maker is a risk neutral,* $\rho_1 = \rho_2 = \rho_3$*;*
*if the decision maker is a strict risk lover,* $\rho_1 < \rho_2 < \rho_3$*;*
*if the decision maker is a middle risk lover,* $\rho_1 = \rho_2 < \rho_3$*;*
*if the decision maker is a primary risk lover,* $\rho_1 < \rho_2 = \rho_3$*;*
*where* $\rho_1 + \rho_2 + \rho_3 = 1$ *and* $\rho_1, \rho_2, \rho_3 > 0$.

**Example 2.** *Consider two known candidates A and B , which are represented by INSs in a universe X given by* $A = \langle [0.4, 0.5][0.2, 0.3][0.3, 0.4] \rangle$ *and* $B = \langle [0.3, 0.4][0.1, 0.2][0.3, 0.4] \rangle$, $C = \langle [0.4, 0.5][0.1, 0.2][0.2, 0.3] \rangle$ *and another ideal pattern* $R = \langle [0.4, 0.5][0.1, 0.2][0.3, 0.4] \rangle$.

*We can choose A, B or C according to the* $D_{AR}$, $D_{BR}$ *and* $D_{CR}$*, where D is defined in Equation (11), and obtain their corresponding values as Table 5 shows:*

**Table 5.** Compare.

| | $\rho_1$ | $\rho_2$ | $\rho_3$ | $D_{AR}$ | $D_{BR}$ | $D_{CR}$ |
|---|---|---|---|---|---|---|
| strict risk averter | 0.7 | 0.2 | 0.1 | 0.011 | 0.020 | 0.007 |
| | 0.6 | 0.3 | 0.1 | 0.013 | 0.018 | 0.007 |
| | 0.5 | 0.4 | 0.1 | 0.015 | 0.017 | 0.007 |
| | 0.5 | 0.3 | 0.2 | 0.013 | 0.017 | 0.011 |
| middle risk averter | 0.4 | 0.4 | 0.2 | 0.015 | 0.015 | 0.011 |
| primary risk averter | 0.4 | 0.3 | 0.3 | 0.013 | 0.015 | 0.013 |
| | 0.6 | 0.2 | 0.2 | 0.011 | 0.018 | 0.011 |
| | 0.8 | 0.1 | 0.1 | 0.007 | 0.021 | 0.007 |
| risk balancer | 1/3 | 1/3 | 1/3 | 0.014 | 0.014 | 0.014 |
| risk lover | 0.1 | 0.2 | 0.7 | 0.011 | 0.007 | 0.020 |
| | 0.1 | 0.3 | 0.6 | 0.013 | 0.007 | 0.018 |
| | 0.1 | 0.4 | 0.5 | 0.015 | 0.007 | 0.017 |
| | 0.2 | 0.3 | 0.5 | 0.013 | 0.011 | 0.017 |
| middle risk lover | 0.3 | 0.3 | 0.4 | 0.015 | 0.011 | 0.015 |
| | 0.2 | 0.2 | 0.6 | 0.011 | 0.011 | 0.018 |
| | 0.1 | 0.1 | 0.8 | 0.007 | 0.021 | 0.007 |
| primary risk lover | 0.2 | 0.4 | 0.4 | 0.013 | 0.013 | 0.015 |

As shown above, different attitudes for risk can affect the distance result, so we can apply this new distance measure to solve the practical problem.

Application and Analysis 2

In this section, we use the TODIM method and the improved interval neutrosophic Euclidean distance with the known parameter of risk preference for decision-making, and then discuss whether different parameter of risk preference $\rho_1$, $\rho_2$, $\rho_3$ affect the decision result. For convenience, we also use the decision information in [43] for application and analysis.

(iv) If decision maker is a strict risk averter, the ranking order is shown in Table 6.

**Table 6.** Strict risk averter.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | Ranking Order | FC |
|---|---|---|---|---|---|---|---|---|
| 0.7 | 0.2 | 0.1 | 0 | 0.925 | 0.615 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.6 | 0.3 | 0.1 | 0 | 0.924 | 0.615 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.5 | 0.4 | 0.1 | 0 | 0.923 | 0.615 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.5 | 0.3 | 0.2 | 0 | 0.931 | 0.627 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(v) If decision maker is a middle risk averter, the ranking order is shown in Table 7.

**Table 7.** Middle risk averter.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | Ranking Order | FC |
|---|---|---|---|---|---|---|---|---|
| 0.4 | 0.4 | 0.2 | 0 | 0.930 | 0.627 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(vi) If decision maker is a primary risk averter, the ranking order is shown in Table 8.

**Table 8.** Primary risk averter.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | **Ranking Order** | **FC** |
|---|---|---|---|---|---|---|---|---|
| 0.4 | 0.3 | 0.3 | 0 | 0.938 | 0.638 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.6 | 0.2 | 0.2 | 0 | 0.932 | 0.627 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.8 | 0.1 | 0.1 | 0 | 0.925 | 0.615 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(vii) If decision maker is a risk neutral, the ranking order is shown in Table 9.

**Table 9.** Risk neutral.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | **Ranking Order** | **FC** |
|---|---|---|---|---|---|---|---|---|
| 1/3 | 1/3 | 1/3 | 0 | 0.939 | 0.641 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(viii) If decision maker is a strict risk lover, the ranking order is shown in Table 10.

**Table 10.** Strict risk lover.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | **Ranking Order** | **FC** |
|---|---|---|---|---|---|---|---|---|
| 0.1 | 0.2 | 0.7 | 0 | 0.959 | 0.677 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.1 | 0.3 | 0.6 | 0 | 0.954 | 0.669 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.1 | 0.4 | 0.5 | 0 | 0.948 | 0.661 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.2 | 0.3 | 0.5 | 0 | 0.931 | 0.658 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(ix) If decision maker is a middle risk lover, the ranking order is shown in Table 11.

**Table 11.** Middle risk lover.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | **Ranking Order** | **FC** |
|---|---|---|---|---|---|---|---|---|
| 0.3 | 0.3 | 0.4 | 0 | 0.943 | 0.648 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.2 | 0.2 | 0.6 | 0 | 0.954 | 0.666 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |
| 0.1 | 0.1 | 0.8 | 0 | 0.964 | 0.684 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

(x) If decision maker is a primary risk lover, the ranking order is shown in Table 12.

**Table 12.** Primary risk lover.

| $\rho_1$ | $\rho_2$ | $\rho_3$ | $A_1$ | $A_2$ | $A_3$ | $A_4$ | **Ranking Order** | **FC** |
|---|---|---|---|---|---|---|---|---|
| 0.2 | 0.4 | 0.4 | 0 | 0.925 | 0.615 | 1 | $A_1 < A_3 < A_2 < A_4$ | $A_4$ |

Compared to Tables 6–12, the ranking order is $A_4$, $A_2$, $A_3$, $A_1$ and $A_4$ is the best choice. This result is the same as that in [43]. It can be seen that the preference parameters have no effect on the decision-making results, but it can affect the overall dominance value of alternatives. We take into consideration the preference behavior of the decision-makers in venture capital, which makes the results more credible and provides some reference for future research.

## 7. Conclusions

In multi-attribute venture capital, according to the fuzzy attributes of decision information, we can use neutrosophic numbers to describe this information, and apply the TODIM method to solve this decision-making problem. In the TODIM method, the distance measure plays a key role. However, the normalized interval neutrosophic Hamming distance, the normalized interval neutrosophic Euclidean distance and the normalized interval neutrosophic Hausdorff distance are usually used in the previous papers, and it is not discussed whether the parameter changes in the normalized generalized model of these formulas will affect the decision-making results. Therefore, this paper first defines the normalized generalized interval neutrosophic Hausdorff distance and the weighted parameter interval neutrosophic distance, and discusses the change of parameters to draw a conclusion that the change of parameters has no effect on the decision-making results. But we can see from the table that different parameter values can affect the overall dominance value of alternatives. Furthermore, considering the preference of the decision maker in venture capital, we add the preference parameters into the distance measure and discuss whether it will affect the decision-making results. This paper divides the preferences of decision-makers into seven categories: strict risk averter, middle risk averter, primary risk averter, risk neutral, strict risk lover, middle risk lover, and primary risk lover. Although it is still shown that preference parameters have no effect on decision-making results, it has effect on the overall dominance value of alternatives. The preference of decision-makers cannot be ignored in the decision-making process. This provides a reference for future research and more application data are needed for further calculation.

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