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Average Distance Measure for TOPSIS-Sine Trigonometric Single-valued Neutrosophic Weighted Aggregation Operator and Its Application in Decision Making

Roliza Md Yasin[1*], Nurul Izzah Wardah Salim[2], Nik Fakhira Nik Ahmad Fuad[3], Noorzahirah Mohd Zahali[4], Suriana Alias[5] and Norzieha Mustapha[6]

[1] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Kelantan, Machang Campus, Kelantan, Malaysia; roliza927@uitm.edu.my
[2] Petronas Gas Berhad, Kertih, Terengganu, Malaysia. E-mail: izzwardah@outlook.com
[3] E-mail: fakhirafuad@gmail.com
[4] E-mail: Noorzahirah00@gmail.com
[5] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Kelantan, Machang Campus, Kelantan, Malaysia, E-mail: suria588@uitm.edu.my
[6] Faculty of Computer and Mathematical Sciences, Universiti Teknologi MARA Kelantan, Machang Campus, Kelantan, Malaysia, E-mail: norzieha864@uitm.edu.my

* Correspondence: roliza927@uitm.edu.my

Abstract: *The aggressive work involved in proposing new distance measures between two neutrosophic sets has been obvious for the past ten years. These continuous efforts are commonly motivated by the need to provide a variety of alternatives in the study of decision-making. This study starts by providing complete proof of the satisfaction of single-valued neutrosophic set properties for a new distance measure. The novel distance measure averages out two different distance measures to reduce the possibility of information loss. Secondary data gathered from a questionnaire survey on the medical emergency knowledge of twenty dental students is used here to become the numerical example for the application of the new distance measure. The single-valued neutrosophic data are then aggregated using a sine trigonometric single-valued neutrosophic aggregator to gain the benefit of preserving the periodicity and symmetry in nature about the origin and eventually satisfying the decision-maker preferences over the multi-time phase parameters. Next, the technique for order of preference by similarity to ideal solution is applied to enable the calculation of the new distance measure resulting in the ranking of the student's knowledge level. Comparative analysis is done with two distance measures using the same aggregation operator and the weighted arithmetic aggregation operator as well. The result shows that regardless of applying different approaches of distance measures, the student who ranks first is the same, concluding in a manner that is consistent with previous findings.*

Keywords: multi-criteria decision making, distance measure, single-valued neutrosophic set, sine trigonometric aggregation operator, technique for order of preference by similarity to ideal solution (TOPSIS)

1 Introduction

Natural language is always subjective, and uncertain when expressing perception or judgment. Probability and statistics have been used for a long time to deal with such subjectivity and uncertainty. Alternatively, uncertainty can be defined as one of the set of variables. The idea of fuzzy set (FS) was proposed by Zadeh [1], and it has since been used in numerous areas, particularly decision-making. However, the outcomes are rarely precise, and decision-makers frequently hesitate. In 1986, Atanassov's work [2] on managing vagueness led to the development of intuitionistic fuzzy sets (IFS). To tackle indeterminacy, Smarandache [3] formulated the neutrosophic set in 1998, while subsequently, Wang et al. [4] introduced the single-valued neutrosophic set (SVNS), tailored for practical application in engineering and scientific investigations. The set considers truth-membership degree, indeterminacy-membership degree, and falsity-membership degree which are independent with one another and lie within the interval [0,1].

Among the numerous studies on the application of fuzzy sets (FS) and intuitionistic fuzzy sets (IFS), notable contributions include those by Zahan [5] and Patel [6], respectively. In neutrosophic environment, Alias and colleagues have put forward several innovative measures in recent years. Mustapha et al. [7] proposed a novel distance measure for SVNS, while in another study[8], they introduced a new entropy weight. Additionally, Alias et al. [9] devised a new roughness similarity measure, all of which were subsequently applied to medical diagnosis problems. Moreover, numerous studies have extended their methodologies into other set theories such as Pythagorean fuzzy soft set [10], picture fuzzy set [11], hesitant fuzzy set [12], plithogenic set [13], and hypersoft set [14].

Aggregation operators (AOs) play a crucial role in solving multi-criteria and group decision-making issues by combining and summarizing data into a single form. In a neutrosophic environment, weighted arithmetic averaging and weighted geometric averaging are commonly defined under different types of sets [15,16,17]. In terms of SVNS, inspired by the ideas of Bonferroni mean, power average, and logarithmic function; new operational laws were defined, and hence, new AOs were proposed by Liu and Wang [18], Yang and Li [19] and Garg and Nancy [20] respectively. Further, as a novel approach to decision-making, Ashraf et al. [21] suggested four aggregation operators under a single-valued neutrosophic environment based on sine trigonometric operational rules.

Multi-criteria decision-making (MCDM) is a popular field of study intending to provide a systematic and rational approach to decision-making in complex and uncertain environments. Further, the use of set theory-based techniques provides decision-makers with powerful tools to handle uncertainty, imprecision, and complexity in MCDM, allowing for more robust and informed decision-making processes [22,23]. TOPSIS is one of the most commonly used classical MCDM methods developed by Hwang and Yoon [24]. The method works by calculating the distances between each evaluation object and the best and worst solution under ideal circumstances to rank the alternatives. The two ideal solutions are defined as positive ideal solution (PIS) and negative ideal solution (NIS) where the satisfactory solution achieved should be as close to the positive ideal solution as possible and as far away as possible from the negative ideal solution. The TOPSIS approach in a single-valued neutrosophic environment was proposed by Biswas et al. [25], and researchers applied it in the many areas such as crowd management, selection problems and risk evaluation [26,27, 28].

Being categorized as a distance-based method, TOPSIS utilizes the Euclidean distance measure of each alternative from the positive and negative ideal solutions to find the best alternative in the field of decision making. This project is inspired by the works of Zeng et al. [29] and Ruzon and Tomasi [30], aims to propose a novel distance measure for single-valued neutrosophic sets. The secondary data from Fernández et al. [31] is used here to become the numerical example for the application of the new distance measure. The data are in the form of questionnaire responses from 20 dental students pertaining to their knowledge levels in diagnosing and giving treatment to dental medical emergencies. The sine trigonometric single-valued neutrosophic aggregation method [21] is used to aggregate all the students' responses to the 24 questions. Then, TOPSIS is employed to produce a ranking of students' knowledge levels in emergency situations, from the most competent to the least knowledgeable. Finally, comparative analysis is performed with some existing distance measures.

The paper is presented in six sections, which start with a comprehensive literature survey on the proposed work. Section 2 reviews the important definitions and properties used in the subsequent section. Then, Section 3 discusses the thorough proving steps of the new average distance measure, which includes the satisfaction of four properties. Next, Section 4 highlights six major steps in performing the TOPSIS procedure with the sine trigonometric single-valued neutrosophic (SVN) weighted aggregation operator following the application of the proposed measure distance. Section 5 provides the analysis with an adequate discussion of the obtained result. Finally, Section 6 concludes the findings of the study with appropriate recommendations for future work.

2. Preliminaries

This section introduces some definitions which guide the explanation in the subsequent sections**.**

Definition 2.1: A Single Valued Neutrosophic Set (SVNS) [4]

Let X be a space of point (objects) and let x be a generic element within X. A truth membership function, $T_A(x)$, an indeterminacy membership function, $I_A(x)$, and a falsity membership function, $F_A(x)$ define a SVNS set A in X. Here $T_A(x)$, $I_A(x)$, $F_A(x)$ are real subsets of [0,1].

$$A = \{\langle x\,;\ T_A(x), I_A(x), F_A(x)\rangle : x \in X\} \tag{1}$$

Definition 2.2: Normalized Euclidean Distance Measure [32]
Let $A = \{x_i, T_A(x), I_A(x), F_A(x): x \in x_i\}$ and $B = \{x_i, T_B(x), I_B(x), F_B(x): x \in x_i\}$ be any two SVNS in X; then the Euclidean distance between SVNS A and B are defined as follow:

$$d(A,B) = \sqrt{\frac{1}{3n}\sum_{i=1}^{n}\left(T_A(x_i) - T_B(x_i)\right)^2 + \left(I_A(x_i) - I_B(x_i)\right)^2 + \left(F_A(x_i) - F_B(x_i)\right)^2} \tag{2}$$

Definition 2.3: Distance Measures on Intuitionistic Fuzzy Sets [29]
Suppose that $A = \{x \in X\}$ and
$B = \{x \in X\}$ are IFS in X, then the distance measure between IFS A and B is defined as follow:

$$d(A,B) = \frac{\sum_{i=1}^{n} d_{e_i}(A,B) \times d_{TF_i}(A,B)}{n} \tag{3}$$

where

$$d_{e_i}(A,B) = e^{\left|T_{A_i}(x_i) - T_{B_i}(x_i)\right| - 1} \tag{4}$$

$$d_{TF_i}(A,B) = \frac{|T_A(x_i) - T_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{2} \tag{5}$$

For these distance measures formula; d_{e_i} denotes the exponential distance measure. d_{TF_i} denotes the average including absolute value of *i*th membership degree and non-membership degree between A and B.

Properties 2.1: The distance measures for intuitionistic fuzzy set $d_{IFS}(A,B)$ satisfies the following properties:

i. $0 \leq d_{IFS}(A,B) \leq 1$
ii. $d_{IFS}(A,B) = 0$ if and only if $A = B$
iii. $d_{IFS}(A,B) = d_{IFS}(B,A)$

iv. $d_{IFS}(A,C) \geq d_{IFS}(A,B)$ and $d_{IFS}(A,C) \geq d_{IFS}(B,C)$ if C is neutrosophic set in X and $A \subseteq B \subseteq C$.

3. An Average Distance Measure for Single-Valued Neutrosophic Set

This section introduces a definition of the average distance measure for SVNS. The properties for a new distance measure are also proven.

Definition 3.1: Let $X = \{x_1, x_2, x_3, \dots, x_n\}$ be a universal set. Then, for two given neutrosophic set, $A = \{x, T_A(x), I_A(x), F_A(x): x \in x_i\}$ and $B = \{x, T_B(x), I_B(x), F_B(x): x \in x_i\}$. The average distance measures for SVNS defined as follows:

$$d_N^{Avg}(A,B) = \frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times d_{TIF_i}(A,B)}{n} \tag{6}$$

where

$$d_{g_i}(A,B) = 1 - exp\,\{(-E_i(A,B))/\gamma\} \tag{7}$$

$$E_i(A,B) = \sqrt{\left(T_A(x_i) - T_B(x_i)\right)^2 + \left(I_A(x_i) - I_B(x_i)\right)^2 + \left(F_A(x_i) - F_B(x_i)\right)^2} \tag{8}$$

$$d_{TIF_i}(A,B) = \frac{|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{3} \tag{9}$$

with $\gamma \in (0, +\infty)$.

The proposed average distance in equation (6) comprises of two distance measures, $d_{g_i}(A,B)$ and $d_{TIF_i}(A,B)$. The former denotes the exponential distance measure [30] where it consists of Euclidean distance, $E_i(A,B)$ divided by γ and the latter denotes the average including the absolute value of the i[th] degree of truth, indeterminacy, and falsity membership for neutrosophic set in between set A and B. Here, Definition 3.1 dictates that the range of exponential, $d_{g_i}(A,B)$ lies between 0 and 1. While $d_{g_i}(A,B)$ approaches a value of 0 due to the zero value of $E_i(A,B)$, it cannot precisely reach the value of 1 because there exists no real number γ such that $exp\left(-\frac{\sqrt{3}}{\gamma}\right)$ equals 1. The proof of property (i) elaborates on this point further. Additionally, as γ decreases, the range of $d_{g_i}(A,B)$ approaches [0,1], as illustrated in Table 1.

Table 1. Different interval values of $d_{g_i}(A,B)$ for various values of γ

γ	**Range of** $d_{g_i}(A,B)$
100	[0.0172,1]
1	[0.8230,1]
0.5	[0.9687,1]
0.4	[0.9868,1]
0.2	[0, 0.9998]
≈ 0	[0, 1)

All properties of distance measures have been satisfied as follows:

Properties 3.1: The novel distance measure for single-valued neutrosophic set $d_N^{Avg}(A,B)$ satisfies the following properties:

i) $0 \leq d_N^{Avg}(A,B) \leq 1$

ii) $d_N^{Avg}(A,B) = d_N^{Avg}(B,A)$

iii) $d_N^{Avg}(A,B) = 0$ if and only if $A = B$

iv) $d_N^{Avg}(A,C) \geq d_N^{Avg}(A,B)$ and $d_N^{Avg}(A,C) \geq d_N^{Avg}(B,C)$ if C is neutrosophic set in X and $A \subseteq B \subseteq C$

The new distance measure satisfies all the properties, and the proofs are given below.

Property i: $0 \leq d_N^{Avg}(A,B) \leq 1$

The degree of truth, indeterminacy, and falsity membership for single-valued neutrosophic set are $0 \leq T_A(x_i), I_A(x_i), F_A(x_i) \leq 1$.

This implies for:

$$A = \{x_i, T_A(x_i), I_A(x_i), F_A(x_i): x_i \in X\}$$
$$B = \{x_i, T_B(x_i), I_B(x_i), F_B(x_i): x_i \in X\}$$

Thus, we have

1) For $d_{g_i}(A,B)$,

$T_A(x_i), T_B(x_i), I_A(x_i), I_B(x_i), F_A(x_i), F_B(x_i) \in [0,1]$.

and

$\left(T_A(x_i) - T_B(x_i)\right)^2$, $\left(I_A(x_i) - I_B(x_i)\right)^2$, and $\left(F_A(x_i) - F_B(x_i)\right)^2 \in [0,1]$

Therefore, we get, Euclidean distance, $E_i(A,B)$

$$= \sqrt{\left(T_A(x_i) - T_B(x_i)\right)^2 + \left(I_A(x_i) - I_B(x_i)\right)^2 + \left(F_A(x_i) - F_B(x_i)\right)^2} \in \left[0, \sqrt{3}\right]$$

Next,

$$\frac{E_i(A,B)}{\gamma} \in \left[0, \frac{\sqrt{3}}{\gamma}\right]$$

and

$$-\frac{E_i(A,B)}{\gamma} \in \left[-\frac{\sqrt{3}}{\gamma}, 0\right]$$

$$exp\left(-\frac{E_i(A,B)}{\gamma}\right) \in \left[exp\left(-\frac{\sqrt{3}}{\gamma}\right), 1\right] \subset (0,1]$$

Then, from equation (7)

$$d_{g_i}(A,B) = 1 - exp\left(\frac{-\sqrt{\left(T_A(x_i) - T_B(x_i)\right)^2 + \left(I_A(x_i) - I_B(x_i)\right)^2 + \left(F_A(x_i) - F_B(x_i)\right)^2}}{\gamma}\right)$$

and obviously

$d_{g_i}(A,B) \in \left[0, 1 - exp\left(\frac{-\sqrt{3}}{\gamma}\right)\right] \subset [0,1]$

$\Rightarrow 0 \leq d_{g_i}(A,B) \leq 1$

2) For $d_{TIF_i}(A,B)$,

$$|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)| \in [0,3]$$

$$\Rightarrow \frac{|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{3} \in [0,1]$$

$\Rightarrow 0 \leq d_{TIF_i}(A,B) \leq 1$

Hence,

$d_{g_i}(A,B) \times d_{TIF_i}(A,B) \in [0,1]$

$$\Rightarrow d_N^{Avg}(A,B) = \frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times d_{TIF_i}(A,B)}{n} \in [0,1]$$

Property ii: $d_N^{Avg}(A,B) = d_N^{Avg}(B,A)$

It is obvious that,

$T_A(x_i) - T_B(x_i) \neq T_B(x_i) - T_A(x_i)$,

$I_A(x_i) - I_B(x_i) \neq I_B(x_i) - I_A(x_i)$, and

$F_A(x_i) - F_B(x_i) \neq F_B(x_i) - F_A(x_i)$

But,

$|T_A(x_i) - T_B(x_i)| = |T_B(x_i) - T_A(x_i)|$,

$|I_A(x_i) - I_B(x_i)| = |I_B(x_i) - I_A(x_i)|$, and

$|F_A(x_i) - T_B(x_i)| = |F_B(x_i) - F_A(x_i)|$

Hence, $d_N^{Avg}(A,B) = \frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times d_{TIF_i}(A,B)}{n} \in [0,1]$

$\Rightarrow d_{g_i}(A,B) \times d_{TIF_i}(A,B)$

$$= 1 - exp\left(\frac{-\sqrt{\left(T_A(x_i) - T_B(x_i)\right)^2 + \left(I_A(x_i) - I_B(x_i)\right)^2 + \left(F_A(x_i) - F_B(x_i)\right)^2}}{\gamma}\right) \times \frac{|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{3}$$

$$= 1 - exp\left(\frac{-\sqrt{\left(T_B(x_i) - T_A(x_i)\right)^2 + \left(I_B(x_i) - I_A(x_i)\right)^2 + \left(F_B(x_i) - F_A(x_i)\right)^2}}{\gamma}\right) \times \frac{|T_B(x_i) - T_A(x_i)| + |I_B(x_i) - I_A(x_i)| + |F_B(x_i) - F_A(x_i)|}{3}$$

$= d_{g_i}(B,A) \times d_{TIF_i}(B,A)$

Hence,

$$\frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times d_{TIF_i}(A,B)}{n} = \frac{\sum_{i=1}^{n} d_{g_i}(B,A) \times d_{TIF_i}(B,A)}{n} = d_N^{Avg}(B,A)$$

Property iii: $d_N^{Avg}(A,B) = 0$ if and only if $A = B$

1) If $A = B$, then
   $T_A(x_i) = T_B(x_i)$,
   $I_A(x_i) = I_B(x_i)$, and
   $F_A(x_i) = F_B(x_i)$.

which means,
   $|T_A(x_i) - T_B(x_i)| = 0$,
   $|I_A(x_i) - I_B(x_i)| = 0$, and
   $|F_A(x_i) - F_B(x_i)| = 0$

Thus,

$$\Rightarrow d_{TIF_i}(A,B) = \frac{|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{3} = 0$$

Hence,

$$\Rightarrow d_N^{Avg}(A,B) = \frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times (0)}{n} = 0$$

2) If $d_N^{Avg}(A,B) = 0$,

$$\Rightarrow \frac{\sum_{i=1}^{n} d_{g_i}(A,B) \times d_{TIF_i}(A,B)}{n} = 0$$

There exist either $d_{g_i}(A,B) = 0$ or $d_{TIF_i}(A,B) = 0$ such that :

(i) $d_{g_i}(A,B) = 1 - exp\left\{\frac{(-E_i(A,B))}{\gamma}\right\} = 0$

$$\Rightarrow exp\left\{\frac{(-E_i(A,B))}{\gamma}\right\} = 1$$

$$\Rightarrow \frac{E_i(A,B)}{\gamma} = 0$$

$$\Rightarrow \sqrt{(T_A(x_i) - T_B(x_i))^2 + (I_A(x_i) - I_B(x_i))^2 + (F_A(x_i) - F_B(x_i))^2} = 0$$

This implies $T_A(x_i) = T_B(x_i)$ and $I_A(x_i) = I_B(x_i)$ and $F_A(x_i) = F_B(x_i)$.
That means, $A = B$.

(ii) $d_{TIF_i}(A,B) = 0$

$$\Rightarrow d_{TIF_i}(A,B) = \frac{|T_A(x_i) - T_B(x_i)| + |I_A(x_i) - I_B(x_i)| + |F_A(x_i) - F_B(x_i)|}{3} = 0$$

Namely, we can have
$|T_A(x_i) - T_B(x_i)| = 0$,
$|I_A(x_i) - I_B(x_i)| = 0$, and
$|F_A(x_i) - F_B(x_i)| = 0$.

Implies $T_A(x_i) = T_B,(x_i)$, $I_A(x_i) = I_B(x_i)$, and $F_A(x_i) = F_B(x_i)$
That means, $A = B$.
Therefore $d_N^{Avg}(A,B) = 0$ if and only if $A = B$

Property iv: $d_N^{Avg}(A,C) \geq d_N^{Avg}(A,B)$ and $d_N^{Avg}(A,C) \geq d_N^{Avg}(B,C)$ if C is neutrosophic set in X and $A \subseteq B \subseteq C$.

Consider we have $C = \{x_i, T_c(x_i), I_c(x_i), F_c(x_i): x_i \in X\}$.
We know that $A \subseteq B$ if an only if $\forall_x \in X$:
$T_A(x_i) \leq T_B(x_i)$ $I_A(x_i) \geq I_B(x_i)$ and
$F_A(x_i) \geq F_B(x_i)$
Let $A \subseteq B \subseteq C$, then we have
$T_A(x_i) \leq T_B(x_i) \leq T_C(x_i)$ $I_A(x_i) \geq I_B(x_i) \geq I_C(x_i)$ and
$F_A(x_i) \geq F_B(x_i) \geq F_C(x_i)$

Then, we can get

$$\Rightarrow 1-exp\left(\frac{-\sqrt{\left(T_A(x_i)-T_C(x_i)\right)^2+\left(I_A(x_i)-I_C(x_i)\right)^2+\left(F_A(x_i)-F_C(x_i)\right)^2}}{\gamma}\right)\geq$$

$$1-exp\left(\frac{-\sqrt{\left(T_A(x_i)-T_B(x_i)\right)^2+\left(I_A(x_i)-I_B(x_i)\right)^2+\left(F_A(x_i)-F_B(x_i)\right)^2}}{\gamma}\right)$$

and

$$\Rightarrow \frac{|T_A(x_i)-T_C(x_i)|+|I_A(x_i)-I_C(x_i)|+|F_A(x_i)-F_C(x_i)|}{3} \geq \frac{|T_A(x_i)-T_B(x_i)|+|I_A(x_i)-I_B(x_i)|+|F_A(x_i)-F_B(x_i)|}{3}$$

That implies $d_{g_i}(A,C)\geq d_{g_i}(A,B)$ and $d_{TIF_i}(A,C)\geq d_{TIF_i}(A,B)$.

Namely, we have $d_N^{Avg}(A,C)\geq d_N^{Avg}(A,B)$

Then, similarly for $d_N^{Avg}(A,C)\geq d_N^{Avg}(B,C)$.

$$\Rightarrow 1-exp\left(\frac{-\sqrt{\left(T_A(x_i)-T_C(x_i)\right)^2+\left(I_A(x_i)-I_C(x_i)\right)^2+\left(F_A(x_i)-F_C(x_i)\right)^2}}{\gamma}\right)\geq$$

$$1-exp\left(\frac{-\sqrt{\left(T_B(x_i)-T_C(x_i)\right)^2+\left(I_B(x_i)-I_C(x_i)\right)^2+\left(F_B(x_i)-F_C(x_i)\right)^2}}{\gamma}\right)$$

and

$$\Rightarrow \frac{|T_A(x_i)-T_C(x_i)|+|I_A(x_i)-I_C(x_i)|+|F_A(x_i)-F_C(x_i)|}{3} \geq \frac{|T_B(x_i)-T_C(x_i)|+|I_B(x_i)-I_C(x_i)|+|F_B(x_i)-F_C(x_i)|}{3}$$

Thus, we can get $d_{g_i}(A,C)\geq d_{g_i}(B,C)$ and $d_{TIF_i}(A,C)\geq d_{TIF_i}(B,C)$, which means $d_N^{Avg}(A,C)\geq d_N^{Avg}(B,C)$.

The proof is completed. ■

4. TOPSIS-Sine Trigonometric SVN Weighted Aggregation Operator with Average Distance Measure

This study follows the steps in [33] but uses different aggregation operator and distance measure. The sine trigonometric aggregator operation by [21] and the new average distance measure are applied here. The secondary data is obtained from [31] regarding the dental students' emergency knowledge in attaining correct diagnosis and providing accurate treatment.

4.1. Data Extraction

The data on the knowledge level of the dental students in medical emergencies are given in the linguistic form with two evaluation criteria i.e diagnosis and treatment knowledge. The students' responses are recorded according to the seven-Likert scale and the associated SVN numbers are assigned to the scales as shown in Table 2. The SVN numbers are placed in two matrices denoted as $X = x_{ij}$ and $Y = y_{ik}$ where i = 1, … , 20 ; j =1, … , 10 and k = 1, … , 14 with $x_{ij} =< T_{ij}, I_{ij}, F_{ij} >$ and $y_{ik} =< T_{ik}, I_{ik}, F_{ik} >$.

Table 2. Linguistic term used [31]

Linguistic Term	SVN Numbers
Excellent (E)	(1,0,0)
Very Good (VG)	(0.80,0.15,0.20)
Good (G)	(0.60,0.35,0.40)
Regular (R)	(0.50,0.50,0.50)
Regular Tending to Bad (RB)	(0.40,0.65,0.60)
Bad (B)	(0.20,0.85,0.80)
Very Bad (VB)	(0,1,1)

4.2. Aggregation of the students' responses

The SVN data is aggregated by using the sine trigonometric aggregation operators [13]. The aggregation calculation of the knowledge level for 20 students in diagnosis and treatment uses equal weights; $w_j = 0.1$ for the 10 diagnosis questions and $w_k = 0.07$ for the 14 treatment questions.

Definition 4.1: Let $A = \{ x_{ij}, y_{ik}, T_A(p), I_A(p), F_A(p): x_{ij} \in X$ and $y_{ik} \in Y \}$ be a SVNS for diagnosis or treatment knowledge evaluation. Then, sine trigonometric weighted averaging aggregation operator for the SVNS (ST-SVNWA) by [21] is defined in equation (10).

$$\text{ST-SVNWA}(A) = \sum_{p=1}^{n} w_p sin(x_p)$$

$$= \left\langle 1 - \prod_{p=1}^{n}\left(1 - sin\left(\frac{\pi}{2}T_{A_p}\right)\right)^{w_p}, \prod_{p=1}^{n}\left(1 - sin\left(\frac{\pi}{2} - I_{A_p}\right)\right)^{w_p}, \prod_{p=1}^{n}\left(1 - sin\left(\frac{\pi}{2} - F_{A_p}\right)\right)^{w_p} \right\rangle \quad (10)$$

The aggregated values are defined in two weighted neutrosophic decision column matrices which denoted by $D^p = \langle d_i^{w_p} \rangle_{20\times1} = \langle T_i^{w_p}, I_i^{w_p}, F_i^{w_p} \rangle_{20\times1}$. At this point forward, the p index will be used to generalize the use of indices j and k representing diagnosis and treatment SVN data values, respectively. If diagnosis SVN numbers are aggregated, w_p equals to w_j and w_p equals to w_k whenever treatment SVN data is aggregated.

4.3. Identify neutrosophic relative positive ideal solution (NRPIS) and neutrosophic relative negative ideal solution (NRNIS)

From each of the two column matrices obtained in the previous subsection, two ideal solutions NRPIS, $d^{w_p^+}$ and NRNIS, $d^{w_p^-}$ are produced by performing the evaluation criteria on benefit-type attribute, J_1 and cost-type attribute, J_2 which defined in equation (11) and (12) [25].

$$d^{w_p^+} = \langle T^{w_p^+}, I^{w_p^+}, F^{w_p^+} \rangle \quad (11)$$

$$d^{w_p^-} = \langle T^{w_p^-}, I^{w_p^-}, F^{w_p^-} \rangle \quad (12)$$

where

$$T^{w_p^+} = \left\{\left(\max_i\{T_i^{w_p}\} | i \in J_1\right), \left(\min_i\{T_i^{w_p}\} | i \in J_2\right)\right\} \; ;$$

$$T^{w_p^-} = \left\{\left(\min_i\{T_i^{w_p}\} | j \in J_1\right), \left(\max_i\{T_i^{w_p}\} | i \in J_2\right)\right\}$$

$$I^{w_p^+} = \left\{\left(\min_i\{I_i^{w_p}\} | i \in J_1\right), \left(\max_i\{I_i^{w_p}\} | i \in J_2\right)\right\};$$

$$I^{w_p^-} = \left\{\left(\max_i\{I_i^{w_p}\} | j \in J_1\right), \left(\min_i\{I_i^{w_p}\} | i \in J_2\right)\right\}$$

$$F^{w_p^+} = \left\{\left(\min_i\{F_i^{w_p}\}|i \in J_1\right), \left(\max_i\{F_i^{w_p}\}|i \in J_2\right)\right\};$$
$$F^{w_p^-} = \left\{\left(\max_i\{F_i^{w_p}\}|j \in J_1\right), \left(\min_i\{F_i^{w_p}\}|i \in J_2\right)\right\}$$

4.4. Calculate the new distance measure for each alternatives

The determination of the new distance measure value in equation (6) requires the calculation of two distance measures in equations (7) and (9). All three equations denote two different neutrosophic sets, A and B. Here, set A is defined as the aggregated decision matrix obtained in subsection 4.2, and set B represents either NRPIS or NRNIS obtained in section 4.3. The whole calculation in this present subsection produces average distance measures for each alternative from NRPIS, D_i^{p+} and average distance measures for each alternative from NRNIS, D_i^{p-}. Since the aggregation process was performed in Section 4.2, Equation (6) has been deduced into Equations (13) and (14), representing D_i^{p+} and D_i^{p-}, respectively.

$$D_i^{p+} = \frac{\sum_{i=1}^{n} d_{g_i}^{p^+}(A, NRPIS) \times d_{TIF_i}^{p^+}(A, NRPIS)}{n} \tag{13}$$

$$D_i^{p-} = \frac{\sum_{i=1}^{n} d_{g_i}^{p^-}(A, NRNIS) \times d_{TIF_i}^{p^-}(A, NRNIS)}{n} \tag{14}$$

4.5. Evaluate the relative closeness coefficient

The relative closeness coefficient denoted by C_i^{p*} in equation (15) ranges between 0 and 1 is determined by the neutrosophic ideal solution for SVNSs for each distance measure.

$$C_i^{p*} = \frac{D_i^{p-}}{D_i^{p+} + D_i^{p-}} \tag{15}$$

Students who obtained $C_i^{p*} > 0.5$ are considered to have higher knowledge of dental medical emergencies compared to those obtained C_i^{p*} less than 0.5.

4.6. Rank the alternative and discuss the analysis

The conclusion on the overall knowledge level of the dental students can be drawn by ranking the values of C_i^{p*} in ascending order. The performance analysis is also done by comparing different distance measures and aggregator operators.

5. Result and Discussion

The study aims to analyze the knowledge level of dental students on medical emergency diagnosis and treatment. The results of the aggregation process by the ST-SVNWA operator on the diagnosis and treatment of dental emergencies data are shown in Table 3.

Table 3. Aggregated sine trigonometric SVN data

Student, S_i	**Diagnosis**	**Treatment**
1	<0.52665, 0.22592, 0.20286>	<0.56978, 0.20318, 0.18640>
2	<0.76036, 0.08690, 0.10208>	<0.92389, 0.01970, 0.03169>
3	<0.59429, 0.18419, 0.17255>	<0.69440, 0.13054, 0.13012>
4	<0.81610, 0.06179, 0.07775>	<0.89869, 0.02807, 0.04231>
5	<0.57312, 0.20396, 0.18166 >	<0.76092, 0.08690, 0.10118>
6	<0.57312, 0.20396, 0.18166>	<0.73688, 0.10208, 0.11160>
7	<0.57312, 0.20396, 0.18166>	<0.67363, 0.14336,0.13939>
8	<0.59461, 0.19379, 0.17191>	<0.72065, 0.11263, 0.11867>
9	<0.81610, 0.06179, 0.07775>	<0.87742, 0.03554, 0.05130>
10	<0.53486, 0.22589, 0.19891>	<0.69986, 0.12537, 0.12787>
11	<0.51831, 0.22594, 0.20688>	<0.60444, 0.18252, 0.17063>
12	<0.54256, 0.21468, 0.19578 >	<0.47846, 0.25181, 0.22864>
13	<0.76036, 0.08690, 0.10208>	<0.91627, 0.02216, 0.03490>
14	<0.49277, 0.23779, 0.21862>	<0.57501, 0.20316, 0.18385>
15	<0.85888, 0.04393, 0.08761>	<0.89869, 0.02807, 0.04231>
16	<0.68773, 0.12222, 0.13402>	<0.88856, 0.03158, 0.04659>
17	<0.50981, 0.22596, 0.21099>	<0.69074, 0.13169, 0.13186>
18	<0.55049, 0.21466, 0.19197>	<0.69074, 0.13169, 0.13186>
19	<0.85888, 0.04393, 0.05922>	<0.88856, 0.03158, 0.04659>
20	<0.50156, 0.23777, 0.21437>	<0.69074, 0.13169, 0.13186>

Based on the aggregated SVN data in Table 3, with $\gamma = 0.2$, the average distance measures, D_i^{j-} and D_i^{j+} per student are computed. Subsequently, the relative closeness coefficient for diagnosis data, C_i^{j*} is determined. The values are shown in Table 4 and compared with the ones obtained using the Euclidean distance measure.

Table 4. Distance and relative closeness coefficient values - Diagnosis

	New Average Distance				Euclidean Distance			
Student, S_i	D_i^{j-}	D_i^{j+}	C_i^{j*}	**Rank**	D_i^{j-}	D_i^{j+}	C_i^{j*}	**Rank**
1	0.00365	0.19035	0.01882	16	0.02264	0.23389	0.08825	16
2	0.14384	0.02699	0.84200	5	0.18970	0.06680	0.73956	5
3	0.03093	0.13788	0.18323	8	0.07142	0.18486	0.27867	8
4	0.18366	0.00583	0.96924	3	0.22757	0.02882	0.88759	3
5	0.01900	0.15644	0.10831	10	0.05467	0.20187	0.21310	10
6	0.01900	0.15644	0.10831	10	0.05467	0.20187	0.21310	10
7	0.01900	0.15644	0.10831	10	0.05467	0.20187	0.21310	10
8	0.02902	0.14086	0.17085	9	0.06950	0.18708	0.27086	9
9	0.18366	0.00583	0.96924	3	0.22757	0.02882	0.88759	3
10	0.00524	0.18566	0.02744	15	0.02770	0.22921	0.10781	15
11	0.00232	0.19514	0.01173	17	0.01761	0.23869	0.06871	17
12	0.00821	0.17748	0.04420	14	0.03433	0.22200	0.13392	14
13	0.14384	0.02699	0.84200	5	0.18970	0.06680	0.73956	5
14	0.00000	0.21373	0.00000	20	0.00000	0.25627	0.00000	20
15	0.20409	0.00125	0.99390	2	0.25085	0.01639	0.93868	2
16	0.09242	0.06882	0.57318	7	0.13967	0.11693	0.54431	7
17	0.00127	0.20001	0.00633	18	0.01276	0.24359	0.04978	18
18	0.01028	0.17293	0.05613	13	0.03906	0.21746	0.15226	13
19	0.21373	0.00000	1.00000	1	0.25627	0.00000	1.00000	1
20	0.00021	0.20870	0.00099	19	0.00564	0.25121	0.02195	19

In Table 4, the ranking for both distance measures give an equivalent result. There are 7 (35%) students (S_2, S_4, S_9, S_{13}, S_{15}, S_{16}, S_{19}) who obtained the values of C^{j*} greater than 0.5 which indicates that they have better understanding in providing correct diagnosis to dental emergencies. Meanwhile, 6 (30%) students (S_1, S_{10}, S_{11}, S_{14}, S_{17}, S_{20}) are ranked at the bottom of the list, showing that they are lacking knowledge in dental emergencies diagnosis. The comparative analysis of the top-ranking students on the dental diagnosis emergency knowledge with the previous studies [31, 33] is illustrated in Table 5.

Table 5. Summary of students' knowledge level on the diagnosis of emergency cases

Techniques	Ranking Order
Scoring function, [31]	$S_{15}, S_{19} > S_4, S_9 > S_2$
Generalized TOPSIS, [33]	$S_{15}, S_{19} > S_2 > S_4, S_9$
ST-SVNWA aggregation operator with average distance	$S_{19} > S_{15} > S_4, S_9 > S_2 > S_{13}$
ST-SVNWA aggregation operator with Euclidean distance	$S_{19} > S_{15} > S_4, S_9 > S_2, S_{13}$
ST-SVNWA aggregation operator with distance measure [7]	$S_{15} > S_{19} > S_4, S_9 > S_2, S_{13}$
Weighted Arithmetic AO with average distance	$S_4, S_9 > S_{19} > S_{15} > S_2, S_{13} >$

The summary result of students' knowledge level in diagnosing patients is shown in Table 5. It highlights the top five ranking of the students derived from different AO and distance measures involving seven students, i.e S_2, S_4, S_9, S_{13}, S_{15}, S_{16}, and S_{19}. It is obvious that students 15 and 19 received the highest score in diagnosing the patient in emergency cases, indicating that both are the most knowledgeable compared to other students.

Table 6 compares the ranking between two distance measures for the dental students' knowledge in giving treatment to dental medical emergencies.

Table 6. Distance and relative closeness coefficient values - Treatment

	New Average Distance				Euclidean Distance			
Student, S_i	D_i^{k-}	D_i^{k+}	C_i^{k*}	**Rank**	D_i^{k-}	D_i^{k+}	C_i^{k*}	**Rank**
1	0.02600	0.20358	0.11324	19	0.06452	0.24698	0.20713	19
2	0.27186	0.00000	1.00000	1	0.31148	0.00000	1.00000	1
3	0.10693	0.10894	0.49534	12	0.15388	0.15773	0.49382	12
4	0.25529	0.00196	0.99237	3	0.29517	0.01651	0.94704	3
5	0.15848	0.06116	0.72156	8	0.20267	0.10940	0.64944	8
6	0.13986	0.07756	0.64326	9	0.18520	0.12668	0.59382	9
7	0.09160	0.12458	0.42373	16	0.13882	0.17274	0.44557	16
8	0.12727	0.08921	0.58790	10	0.17332	0.13845	0.55591	10
9	0.24107	0.00634	0.97436	7	0.28130	0.03052	0.90212	7
10	0.11157	0.10436	0.51669	11	0.15828	0.15341	0.50782	11
11	0.04554	0.17679	0.20483	17	0.08951	0.22201	0.28735	17
12	0.00000	0.27186	0.00000	20	0.00000	0.31148	0.00000	20
13	0.26689	0.00019	0.99930	2	0.30657	0.00498	0.98403	2

14	0.02805	0.20058	0.12270	18	0.06756	0.24394	0.21689	18
15	0.25529	0.00196	0.99237	3	0.29517	0.01651	0.94704	3
16	0.24855	0.00376	0.98508	5	0.28857	0.02317	0.92567	5
17	0.10454	0.11135	0.48424	13	0.15150	0.16014	0.48615	13
18	0.10454	0.11135	0.48424	13	0.15150	0.16014	0.48615	13
19	0.24855	0.00376	0.98508	5	0.28857	0.02317	0.92567	5
20	0.10454	0.11135	0.48424	13	0.15150	0.16014	0.48615	13

In Table 6, there are 11 (55%) students who obtained values C^{k*} of greater than 0.5 for both distance measures, which indicates that they have a better understanding in giving correct treatment to dental emergencies. Among these 11 students, 7 (S_2, S_4, S_9, S_{13}, S_{15}, S_{16}, and S_{19}) of them are the same students that acquired the higher C^{k*} values in Table 3. Meanwhile, there are 4 (20%) of the same students who are ranked at the bottom of the list, showing that they lack knowledge in dental emergency treatment. Obviously, the two same students (S_{11}, S_{14}) obtain lower C^{k*} values in both Table 4 and Table 6.

The comparative analysis of the top-ranking students, on the dental treatment emergency knowledge with the previous studies [31, 33] is illustrated in Table 7.

Table 7. Summary of students' knowledge level on the treatment of emergency cases

Techniques	Ranking Order
Scoring function, [31]	$S_2 > S_{13} > S_4 > S_{15} > S_9$
Generalized TOPSIS, [33]	$S_2 > S_{13} > S_4 > S_{15} > S_{16}$
Sine trigonometric weighted averaging AO with average distance	$S_2 > S_{13} > S_4, S_{15} > S_{16}, S_{19}$
Sine trigonometric weighted averaging AO with Euclidean Distance	$S_2 > S_{13} > S_4, S_{15} > S_{16}, S_{19}$
Sine trigonometric weighted averaging AO with distance measure [7]	$S_2 > S_{13} > S_4, S_{15} > S_{16}, S_{19}$
Weighted Arithmetic AO with average distance	$S_2 > S_{13} > S_4, S_{15} > S_{16}, S_{19}$

From Table 7, the same seven students are listed as the top five students when compared to the findings in Table 5. Here, it is obvious that student 2 is identified as the most knowledgeable in giving correct emergency treatment for all techniques of measurement. The use of two AOs for two different distance measures results in the equivalent ranking of the top four students (S_2, S_{13}, S_4, and S_{15}).

6. Conclusion and Recommendation

In this work, a new distance measure has been proposed for use with the TOPSIS approach in ranking the level of dentistry students' knowledge in medical emergencies, applying the existing data from [31]. The new distance measures for single-valued neutrosophic sets are developed and demonstrated in this study. The effectiveness of the new distance measure formula is analyzed, and it is found to be consistent with the existing distance measures. The analyses demonstrate the effectiveness of the novel distance-based similarity measure for truth, indeterminacy, and falsity membership functions.

In this task, a sine trigonometric weighted averaging aggregation operator [21] is applied. It is found that this aggregation operator is significantly efficient for handling uncertainty in decision-making problems. The functionality of this method is tested by determining the level of knowledge of dentistry students in medical emergencies. To evaluate its performance, a comparison with several published works is conducted. The outcome of the investigation demonstrates that it is reliable due to the consistency of the findings with the previous studies.

The method approach used in this work is believed to create more opportunities for future research in the field of neutrosophic decision-making. It will be applied to other uncertain fields, such as risk analysis, fault diagnosis, and evaluation systems.

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