INTUITIONISTIC FUZZY MULTICRITERIA DECISION MAKING TECHNIQUES AND ITS APPLICATION TO MENTAL HEALTH DIAGNOSIS

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Abstract: Decision making in medical diagnosis is becoming an important study topic in medical technology. From existing study and understanding in medical science, the primary and minor symptoms of virtually every disease are documented. In the early stages of any sickness, the symptoms of the patient are carefully examined, and by comparing the symptoms, it is possible to deduce the ailment that the patient may be suffering from. Consequently, an effort has been undertaken to implement a fuzzy decision-making strategy based on intuitionistic fuzzy sets. Uncertainty is a factor that makes decision-making more challenging in scientific research. Everyone differs from one another on both a physical and an intellectual level; the indicators of illness revealed by patients are linguistic in character and vary from person to person. For instance, the pain experienced by a patient with a serious brain injury is frequently communicated using linguistic phrases such as a great deal, an excessive lot, acute, etc. A medical professional makes a diagnosis based on the symptoms and signs provided by a patient in order to determine a possible condition. Due to this, scientific diagnosis involves decision-making under uncertainty. In the past few decades, similarity measure has played a significant role in selection technology. Similarity is commonly used to determine the similarity and relationship between two objects. Various similarity measures on intuitionistic fuzzy sets (IFSs) have been developed by numerous scholars and implemented in scientific diagnosis throughout the past few decades. In this paper, we are able to generalize and construct a new similarity measure within the setting of intuitionistic fuzzy sets by employing the fuzzy idea. We provide various examples to support the proposed similarity measures between IFSs. For the performance and reliability of the suggested similarity measure, a comparison examination of numerical instances is conducted. Moreover, the similarity metric is integrated into a multi-criteria decision-making strategy. In addition, we employ our similarity metric between two IFSs to build the intuitionistic fuzzy technique of ordered preference similarity of ideal solution (IF-TOPSIS) method. We use our IF-TOPSIS algorithm to identify mental health issues that involve a complex multicriteria decision-making process. The discussion concludes with a discussion of a medical diagnosis problem in an intuitionistic fuzzy environment.

Keywords: Fuzzy Sets, Intuitionistic Fuzzy Sets, Similarity Measures, Multicriteria Decision Making Problems, Medical Diagnosis, IF-TOPSIS.

1. INTRODUCTION

Elements in a crisp set have a Boolean state of obedience indicating either membership or non-membership. Simply a crisp set represented by feature characteristics that allocates a value of 0 or 1 to every detail of the universe, distinguishing between contributors and non-contributors to the crisp set under consideration. In the framework of the fuzzy set precept, we frequently seek assistance from "classic" or "everyday" technologies. This accurate and deterministic idea no longer works. It may also be used in everyday situations when "less" or "greater" or "very low" or "very high" is necessary. To address such circumstances in the real world, the fuzzy set concept is utilized. In fuzzy set principle, step-by-step various values are employed in lieu of specified or sharp values. Prof. L.A. Zadeh (Zedah,1965) introduced the concept of addressing uncertainty. The membership degree of an element in a fuzzy set is a real number in the interval [0, 1]. For every element of a fuzzy set, the membership and non-membership values are added together to equal 1. By relaxing this constraint, Atanassov (Atanassov,1986) conceived of the Intuitionistic fuzzy set to provide a more accurate representation of uncertainty. For an Atanassov's Intuitionistic fuzzy set (IFS), the membership degree and non-membership degree are both real numbers in the interval [0,1], and their sum is less than 1. The difference between 1 and their summing results in another IFS metric, namely the degree of reluctance. As a result of incorporating the degree of belongingness, degree of non-belonging, and hesitancy margin, the information and semantic depiction of IFS become more creative and relevant in a variety of domains, in addition to being intriguing and useful. (Szmidt and Kacprzk, 2004) demonstrated that IFSs are very useful in coping with uncertainty, and that IFSs have attracted the interest of numerous researchers in recent years. This is particularly due to the fact that IFSs are consistent with human behavior and are capable of reflecting and modeling the uncertainty present in real-life situations. IFS theory is implemented in numerous fields, including decision-making, logical programming, clinical diagnosis, and pattern recognition. Similarity measure plays a crucial role in the application of fuzzy units and intuitionistic fuzzy sets and it is a valuable tool for determining the similarity of things. Since many various degrees of similarity between IFSs have been reported in the literature, we propose a number of cost-effective methods for calculating the degree of similarity between IFSs.

Fuzzy Set Theory (FST) was initially developed by (Zadeh, 1965). The first book on fuzzy sets and fuzzy logic mathematics, "Fuzzy Sets," by Lotfi A. Zadeh, appeared in 1965. He described the operation of membership functions in the [0, 1] space (Ramot et al., 2002). Some similarity measures developed by fuzzy set theory have several uses in the fields of medicine, Researchers Ashraf and Beg, Chuntian and Dengfeng, Wang et al., and Xia and Xu studied into the comparability and effects of these multiple fuzzy similarity measures. Cross and Sudkamp introduced the idea of similarity by defining fuzzy valued assessment of the similarity of fuzzy sets (Pedrycz, 1990). (Atanassov, 1986) established the system of IFS as an extension of the standard fuzzy set principal. Entropy for hesitant fuzzy sets based on Hausdorff metric with construction of hesitant fuzzy TOPSIS (Hussain and Yang, 2019). Distance and similarity measures of hesitant fuzzy sets based on Hausdorff metric with applications to multi-criteria decision making and clustering (Yang and Hussain, 2019). Fuzzy entropy for Pythagorean fuzzy sets with application to multicriteria decision making given by (Yang & Hussain, 2018). Distance and similarity measures of Pythagorean fuzzy sets based on the Hausdorff metric with application to fuzzy TOPSIS suggested by (Hussain & Yang, 2019). Dubois et al. explained several terminological difficulties in fuzzy set theory and intuitionistic fuzzy set theory (Mahmood, 2020). (Szmidt and Kacprzyk (Szmidt et al., 2004) demonstrated that IFSs are very useful in coping with uncertainty, and that IFSs have attracted the interest of numerous researchers in recent years. Belief and plausibility measures on intuitionistic fuzzy sets with construction of belief-plausibility TOPSIS suggested by (Yang et al., 2020). Analysis of critical causes of transaction cost escalation in public sector construction projects (Ali et al. 2020). Similarity measures of Pythagorean fuzzy sets with applications to pattern recognition and multicriteria decision making with Pythagorean TOPSIS proposed by (Hussain et al., 2021). Hausdorff distance and similarity measures for single-valued neutrosophic sets with application in multi-criteria decision making (Ali et al., 2022). Distances and Similarity Measures of Q-Rung Orthopair Fuzzy Sets Based on the Hausdorff Metric with the Construction of Orthopair Fuzzy TODIM (Hussain et al., 2022). Wiener index for an intuitionistic fuzzy graph and its application in water pipeline network (Dinar et al., 2023).

Belief and plausibility measures on Pythagorean fuzzy sets and its applications with BPI-VIKOR (Hussain et al., 2023). One of the main reasons IFS has been regarded as a more potent and effective notion than the FST to cope with ambiguity in decision-making is because of this. Researchers have worked extremely hard in recent years to demonstrate the effectiveness of IFS in uncertainty modeling problems and its applicability in a wide variety of fields, including judgment, fuzzy optimization, sample reputation, medical diagnosis, and numerous other topics. Simple standards and definitions of Intuitionistic fuzzy set theory are defined in the opening section. It has been found that when assessing the degree of similarity amongst IFSs, a unique similarity metric yields different values). A new axiomatic definition of a similarity measure for IFSs was presented by Li et al. With the help of, an axiomatic method of the IFS modified similarity measure was devised (Li et al.,2007). A few similarity measures on IFSs were developed by (Li et al., 2002), (Liang et al., 2003), (Li et al., 2007), and (Xu, 2007) Measures of distance and similarity have some value and importance while making decisions. Similarity Measure between Pythagorean Fuzzy Sets based on Lower, Upper and Middle Fuzzy Sets with Applications to Pattern Recognition and Multicriteria Decision Making with PF-TODIM (Hussain et al., 2023). Similarity measures of Pythagorean fuzzy sets based on L_p metric and its applications to multicriteria decision-making with Pythagorean VIKOR and clustering (Hussain et al., 2023). Application of q-Rung Orthopair Fuzzy Entropy Measures to Multicriteria Decision Making and Medical Diagnosis (Hussain et al., 2023). Novel Distance and Similarity Measure on Pythagorean Fuzzy Sets and its Application to Multicriteria Decision Making with ELECTRE Method for Selection of Best Mobile Phones (Hussain et al., 2023). New Divergence Model in Intuitionistic Fuzzy Sets for Decision Making (Rahman et al., 2023). It is frequently crucial to develop better metrics for better decision-making. With the assistance of numerous researchers, a number of similarity metrics have been presented on IFS Numerous scholars have also examined, improved severe similarity metrics that are used in a variety of decision-making scenarios. Numerous studies have been conducted to develop aids for medical diagnostics that use fuzzy similarity and fuzzy distance degree. Although there are many different similarity measures used in literature, it is usually necessary to have a significant number of similarity measures to check and validate the results using specific similarity measures to obtain more accurate and useful results. For a few IFSs, current similarity measurements may fail to provide accurate and immediate result. A new similarity degree on an intuitive fuzzy set has been supplied in this project in chapter four, the elements and definitions of popular and contemporary similarity metrics are provided. To deal with uncertainty in decision-making problems using the IFS idea, the similarity measure is crucial equipment. Great researchers have proposed a variety of similarity measurements. Additionally, the findings from a more thorough study are irrelevant and contradict each other. demonstrating that the suggested similarity measure fits all prerequisites. The literature summary on current study of clinical prognosis utilizing IFS, A modern similarity degree on Intuitionistic fuzzy devices has been proposed in the next phase, Section 4, and it has been demonstrated that the proposed dissimilarity degree meets all similarity axioms. In chapter four, a technique for identifying the likely mental conditions experienced by any affected person using Intuitionistic fuzzy sets and the proposed similarity measure was discussed. Phase 5 has developed a discussion at the achieved quit result and compared it to current and recent research, finding that the recommended similarity degree yields more useful results.

The remaining portion of paper is organized as follows: In Section 2, we review some basic concepts of IFSs. In Section 3, we put forward a novel similarity measure between IFSs. Also, we use some examples with comparison to existing similarity to show the reasonability of our method. Section 4, is dedicated to application of proposed similarity in mental health diagnosis involving multi-criteria decision-making process with TOPSIS. Finally, conclusion is stated in Section 5.

2. BASIC NOTIONS

In this section, we focus on fundamental definitions and operations on IFSs. Further, we briefly discuss the recent development regarding distance and similarity between two IFSs.

Definition 1. (Atanassov, 1986, 1999). An IFS C in X is mathematically denoted by

$$C = \left\{ (x, \mu_c(x), \nu_c(x) \mid x \in X \right\}$$

where $\mu_c(x) :\to [0,1], \nu_c(x) : X \to [0,1]$ with the condition that $0 \le \mu_c(x) + \nu_c(x) \le 1, \ \forall \ x \in X$. Here $\mu_{\hat{c}}(x)$ and $\nu_{\hat{c}}(x)$ denoted the membership and non-membership degree $\hat{C}$ and $\pi_{\hat{c}}(x)$ is degree hesitancy respectively.

Definition 2 (Hussain & Yang,) If C and D are two IFSs of the set X then

(i) $C \subseteq D$ if and only if $\forall\ x \in X$, $\mu_C(x) \le \mu_D(x)$ and $\nu_C(x) \ge \nu_D(x)$;

(ii) $C = D$ if and only if $\forall\ x \in X$, $\mu_C(x) = \mu_D(x)$ and $\nu_C(x) = \nu_D(x)$;

(iii) $C \cup D = \left\{x, \left(max\left(\mu_C(x),\ \mu_D(x)\right), min\left(\nu_C(x),\ \nu_D(x)\right)\right)\right\}, \forall\ x \in X$;

(iv) $C \cap D = \left\{x, \left(min\left(\mu_C(x),\ \mu_D(x)\right), max\left(\nu_C(x),\ \nu_D(x)\right)\right)\right\}, \forall\ x \in X$;

(iv) $C^c = \left\{x, \nu_C(x), \mu_C(x), \forall\ x \in X\right\}$.

The similarity measure is an important tool that can be used in hard decision to deal with uncertainty using the IFS idea.

Definition 3. Let C, D and F are three fuzzy sets on universe of discourse X. A function $S : IFS(X) \times IFS(X) \to [0,1]$ is called similarity between two IFSs if it satisfies the following axioms.

(H_1) $0 \le S(C,D) \le 1$;

(H_2) $S(C,D) = 1$ *if and only if* $C = D$;

(H_3) $S(C,D) = S(D,C)$;

(H_4) *If* $C \subseteq D \subseteq F$ *then* $S(C,F) \le S(C,D)$ *and* $S(C,F) \le S(D,F)$.

Recently, the similarity between IFSs in the literature is given as follows:

$$S_i(C,D) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{3 + min(\mu_C(x_i), \mu_D(x_i))}{4} - \frac{max(\nu_C(x_i), \nu_D(x_i))}{4} - \frac{\left|\mu_C(x_i) - \mu_D(x_i)\right| + \left|\nu_C(x_i) - \nu_D(x_i)\right|}{4}\right) \quad (1)$$

3. Novel similarity between IFSs

This section is dedicated to construct novel similarity between two IFSs. Similarity measure between IFSs is very important duet to its wide range applications in many fields od day to day life including pattern recognition and multi criteria decision making. Suppose $C \, and \, D$ are two IFSs on X. The novel similarity between two IFSs is defined as follows:

$$S_{Mj}(C,D)=\sum_{i=1}^{n}\frac{2min\left(min\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)\right)}{min\left(min(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D((x_i)\right)+max\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),min\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)} \quad (2)$$

The normalized version of Eq. (1) can be defined as

$$S_{Mj}\left(C,D\right)=\frac{1}{n}\sum_{i=1}^{n}\frac{2min\left(min\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)\right)}{min\left(min(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D((x_i)\right)+max\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),min\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)} \quad (3)$$

In applications and ranking of alternatives weight vector w of the element $x \in X$ is usually considered. Therefore, we use Eq. (3) to establish new weighted similarity measure between two IFSs. Suppose that the weight of every element $x_i \in X$ is $w_i \left(i=1,2,3,...,n\right)$ such that $\sum_{i=1}^{n} w_i = 1$, where $0 \le w_i \le 1$, new weighted similarity measure between two IFSs is given as follows:

$$S_{Mj}\left(C,D\right)=\sum_{i=1}^{n}w_i\frac{2min\left(min\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)\right)}{min\left(min(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),max\left(\nu_C\left(x_i\right),\nu_D((x_i)\right)+max\left(\mu_C\left(x_i\right),\mu_D\left(x_i\right)\right),min\left(\nu_C\left(x_i\right),\nu_D\left(x_i\right)\right)} \quad (4)$$

Remark 1. The Eq. (4) become a Eq. (3) if we replace $w_i = \frac{1}{n}$, for $i = 1, 2, ..., n.$ Consequently, Eq. (3) become the special case of Eq. (4).

3.1. **Numerical examples and Comparison of similarity measures**

In this subsection, we compare our proposed similarity measures Eq. (3) with recently developed similarity between IFSs Eq. (1). Our proposed similarity measure Eq. (3) is quite simple and easy to handle the vague information as compare to the latest one Eq. (1). The computational comparison is calculated as follows:

Example 1. Let C and D are two IFSs on universe of discourse X, where

$$C = \{\langle x_1, 0.3, 0.3\rangle, \langle x_2, 0.4, 0.4\rangle\} \textit{ and } D = \{\langle x_1, 0.4, 0.5\rangle, \langle x_2, 0.2, 0.7\rangle\}.$$

The similarity between IFSs C and D using Eq. (1) is given by $S_i(C, D) = 1.125$. We see that the result given by Eq. (1) is not acceptable as it violates the similarity axiom (H_1) of Definition 1. On the other hand, the similarity between IFSs C and D utilizing our proposed method Eq.(3) is $S_{Mj}(C, D) = 0.7718$, which is according to our intuition and satisfy the axiom (H_1) of Definition 1. For further clarification, we consider the following Example 2.

Example 2. Let C and D are two IFSs on universe of discourse X, where

$$C = \{\langle x_1, 0.4, 0.4\rangle, \langle x_2, 0.5, 0.5\rangle\} \textit{ and } D = \{\langle x_1, 0.4, 0.4\rangle, \langle x_2, 0.5, 0.5\rangle\}.$$

The similarity between IFSs C and D using Eq. (1) is given by $S_i(C, D) = 1.51$. We see that the IFSs C and D are exactly equal and similarity between them must be equal to 1. Thus, Eq. (1) is failed to produce expected result. On the other hand, the similarity between IFSs C and D utilizing our proposed method Eq. (3) gives accurate results $S_{Mj}(C, D) = 1.000$, which is reasonable and fulfils the requirements of similarity axiom (H_2) of Definition 1.

Now, we consider the degenerated cases of IFSs for further clarification and comparison as follows.

Example 1.2.7. Let C and D are two IFSs on universe of discourse X, where the degenerated cases of IFSs are given as

$$C = \{\langle x_1, 0, 1\rangle, \langle x_2, 0, 1\rangle\} \text{ and } H = \{\langle x_1, 1, 0\rangle, \langle x_2, 1, 0\rangle\}.$$

The similarity measure of degenerated IFSs must be zero because they are entirely opposite sets. On contrary, the result using Eq. (1) is $S_i(C,D)=1$. On the other hand, our proposed similarity method Eq. (2) gives accurate results $S_{Mj}(C,D)=0$. The comparison Table is given as follows:

Table 1. *Comparison of IFSs*

$IFSs$	S_{Mj}	S_i
$S(C,D)$	0.7718	1.125
$S(C,D)$	1	1.51
$S(C,D)$	0	1

Through numerical comparison mentioned in Table 1, we able to conclude that the new similarity measure Eq. (2) is more effective at handling counterintuitive circumstances than the existing similarity measures.

4. Application proposed similarity in mental health diagnosis involving multi-criteria decision-making process

The pressures and difficulties that students face during their time in college are a transitory period (Bayram & Bilgel, 2008; Grayson, 1989), and as a result, they may develop mental health issues. It might not be fair to categorize people as having mental problems in light of the changing demands and stresses. Furthermore, the prevalence rate varies greatly, mostly as a result of the various evaluation methods, severity cut - offs, and operational definitions of mental health issues.

25 participants were selected by non-probability consecutive sampling for a cross-sectional study at our university. A web-based, cross-sectional study was carried out among students from several departments at KIU in addition to a questionnaire designed to assess the general perception of mental health concerns, their symptoms, and diseases. The present study was undertaken to highlight the effects of psycho logic on students. Google forms were utilized to distribute the online questionnaire to assess anxiety, depression, eating disorders, substance misuse, sources of distress, and coping mechanisms. Stress, anxiety, depression-like symptoms, eating disorders, and other

psychological concerns are frequently reported by university students as having a substantial detrimental impact on their academic performance and mental health.

The capacity to reason and act on ambiguous and subjective information is a crucial component of human decision-making. Humans have an amazing capacity for adaptability when it comes to speech recognition, sloppy handwriting, and abstract thought. Vagueness, ambiguity, and imprecision have not stopped human beings from acting, and human communication frequently uses linguistic terms rather than the precise numeric data required by compilers. The human brain's poorly understood traits, such as its capacity for global reasoning and several levels of pattern recognition, account for a large portion of this variance (Zadeh, 1972). Until a point is reached beyond which accuracy and significance (or relevance) become properties that are mutually exclusive, as systems become more complicated, our ability to make exact and yet significant statements about their behavior declines. A multi-criteria medical diagnosis challenges are conducted in order to demonstrate the validity and usefulness of the suggested distance measure in real-world scenarios.

A decision-making problem is a method for selecting the best choice from a list of viable alternatives.

Step 1: Let us consider a set of n alternatives $H_1, H_2, H_3, ..., H_n$ with $K_1, K_2, K_3, ..., K_m$ are the m criteria for each alternative. The ratings e_{ij} of each criteria $K_j\left(1,2,...,m\right)$ for each alternatives $H_i\left(i=1,2,...,n\right)$ are assign through IFSs. Thus, the relation of alternatives and criteria can be expressed in the matrix format as follows:

$$\begin{array}{c} \\ H_1 \\ H_2 \\ \vdots \\ H_n \end{array} \begin{array}{c} \begin{array}{cccc} K_1 & K_2 & \cdots & K_m \end{array} \\ \begin{bmatrix} \grave{e}_{11} & \grave{e}_{12} & \cdots & \grave{e}_{1m} \\ \grave{e}_{21} & \grave{e}_{22} & \cdots & \grave{e}_{2m} \\ \vdots & \vdots & \vdots & \vdots \\ \grave{e}_{n1} & \grave{e}_{n2} & \cdots & \grave{e}_{nm} \end{bmatrix} \end{array}$$

Step 2: Weightings of the various criteria for a certain group using IFS $\widehat{w}_{jz};\ \ j=1,2,...,m;\ \ z=1,2,...,t$ of different criteria K_j are obtained from the expert committee for membership in a particular group. The matrix allows for the expression of the weight.

The expert committee provides the weights for the various requirements for membership in a certain group. In the resulting matrix, the weight can be stated as follows:

$$\begin{array}{c} \\ K_1 \\ K_2 \\ \vdots \\ K_m \end{array}\begin{array}{c} \begin{array}{cccc} O_1 & O_2 & \cdots & O_z \end{array} \\ \begin{bmatrix} \widehat{w}_{11} & \widehat{w}_{12} & \cdots & \widehat{w}_{1z} \\ \widehat{w}_{21} & \widehat{w}_{22} & \cdots & \widehat{w}_{2z} \\ \vdots & \vdots & \vdots & \vdots \\ \widehat{w}_{m1} & \widehat{w}_{m2} & \cdots & \widehat{w}_{mz} \end{bmatrix} \end{array}$$

Step 3: Determine the degree to which the ratings of the alternatives and the corresponding criterion's weights are similar. The following matrix format can be used to establish the relationship between the alternatives and the different groups:

$$\begin{array}{c} \\ H_1 \\ H_2 \\ \vdots \\ H_n \end{array}\begin{array}{c} \begin{array}{cccc} O_1 & O_2 & \cdots & O_z \end{array} \\ \begin{bmatrix} \dot{s}_{11} & \dot{s}_{12} & \cdots & \dot{s}_{1z} \\ \dot{s}_{21} & \dot{s}_{22} & \cdots & \dot{s}_{2z} \\ \vdots & \vdots & \vdots & \vdots \\ \dot{s}_{n1} & \dot{s}_{n2} & \cdots & \dot{s}_{nz} \end{bmatrix} \end{array}$$

where the weights assigned to the criteria for group membership take into account how similar the alternative is.

Step 4: If there is a greater similarity, the alternative is thought to be closer to the desired group. As a result, sort the alternatives based on how similar they are in decreasing order.

CASE STUDY

Case Study 1: Two hypothetical case studies have been conducted in this section to perform medical diagnosis using the idea of IFSs based on the proposed similarity measure. Here, it is suggested to consider the three parameters that describe IFSs: the degree of membership, the degree of non-membership, and the degree of decision maker hesitancy.

Let $F = \{P_1, P_2, P_3, P_4, P_5\}$ be the collection of students, T= {Stress, Hopelessness, feeling of guilt, difficulty for decision, avoiding friends, thought just dying is solution} be the sets of symptoms, D = {Depression, Anxiety, Suicidal ideation, Eating disorder, Substance abuse}be the sets of disorders/diseases.

Our intentions are to implement each student's right decision, $F_i\,(i = 1, 2, 3, 4, 5)$. From the collection of symptoms $T_j\,(j = 1, 2, 3, 4, 5, 6, 7)$ For each Illness $P_k\,(k = 1, 2, 3, 4, 5)$.

The symptoms of the patient Intuitionistic fuzzy relation $F \to T$ and symptoms-disease Intuitionistic fuzzy relation $T \to P$ are provided in Table A and Table B respectively.

Table 2: patient–symptoms Intuitionistic fuzzy relation $F \to T$

$F \to T$	*Stress* (St)	*Feeling of Guilt* (Fg)	*Difficult for decision* (Dc)	*Avoiding friends , family* (Af)	*Thoughts of Dying to solve problems* (Td)
P_1	$(0.4, 0.2)$	$(0.5, 0.3)$	$(0.2, 0.7)$	$(0.4, 0.4)$	$(0.1, 0.4)$
P_2	$(0.6, 0.3)$	$(0.7, 0.1)$	$(0.2, 0.8)$	$(0.3, 0.3)$	$(0.1, 0.9)$
P_3	$(0.7, .02)$	$(0.1, 0.7)$	$(0.3, 0.6)$	$(0.2, 0.5)$	$(0.0, 0.8)$
P_4	$(0.5, 0.1)$	$(0.8, 0.2)$	$(0.1, 0.7)$	$(0.6, 0.1)$	$(0.2, 0.6)$
P_5	$(0.5, 0.0)$	$(0.4, 0.1)$	$(0.2.0.3)$	$(0.4, 0.1)$	$(0.1, 0.7)$

Table 3: symptom-disease Intuitionistic fuzzy relation

$F \to T$	Depression	Anxiety disorder	Suicidal ideation	Eating disorder	Substance Abuse
Stress (St)	$(0.1, 0.5)$	$(0.2, 0.6)$	$(0.1, 0.6)$	$(0.2, 0.7)$	$(0.3, 0.6)$
Feeling of Guilt (Fg)	$(0.5, 0.1)$	$(0.4, 0.1)$	$(0.7, 0.1)$	$(0.5, 0.1)$	$(0.6, 0.1)$
Difficult for decision (Dc)	$(0.6, 0.2)$	$(0.1, 0.7)$	$(0.3, 0.6)$	$(0.2, 0.5)$	$(0.1, 0.4)$
Avoiding friends, family (Af)	$(0.5, 0.1)$	$(0.2, 0.6)$	$(0.1, 0.4)$	$(0.6, 0.3)$	$(0.8, 0.2)$
Thoughts of Dying to solve problems (Td)	$(0.6, 0.3)$	$(0.3, 0.7)$	$(0.1, 0.4)$	$(0.6, 0.3)$	$(0.5, 0.3)$

Now we represent the intuitionistic similarity measure between patient and the disease can be calculated using Eq. (2) as follows:

$S_{Mj}(P_1, Dp) = 0.45456;$ $S_{Mj}(P_2, Dp) = 0.711;$ $S_{Mj}(P_3, Dp) = 0.4872;$

$S_{Mj}(P_4, Dp) = 0.0844;$ $S_{Mj}(P_5, Dp) = 0.6436.;$.

$S_{Mj}(P_1, Ax) = 0.5468;$ $S_{Mj}(P_2, Ax) = 0.5234;$ $S_{Mj}(P_3, Ax) = 0.6714;$

$S_{Mj}(P_4, Ax) = 0.5079;$ $S_{Mj}(P_5, Ax) = 0.9332.$

$S_{Mj}(P_1, Ed) = 0.5470;$ $S_{Mj}(P_2, Ed) = 0.4728;$ $S_{Mj}(P_3, Ed) = 0.6594;$

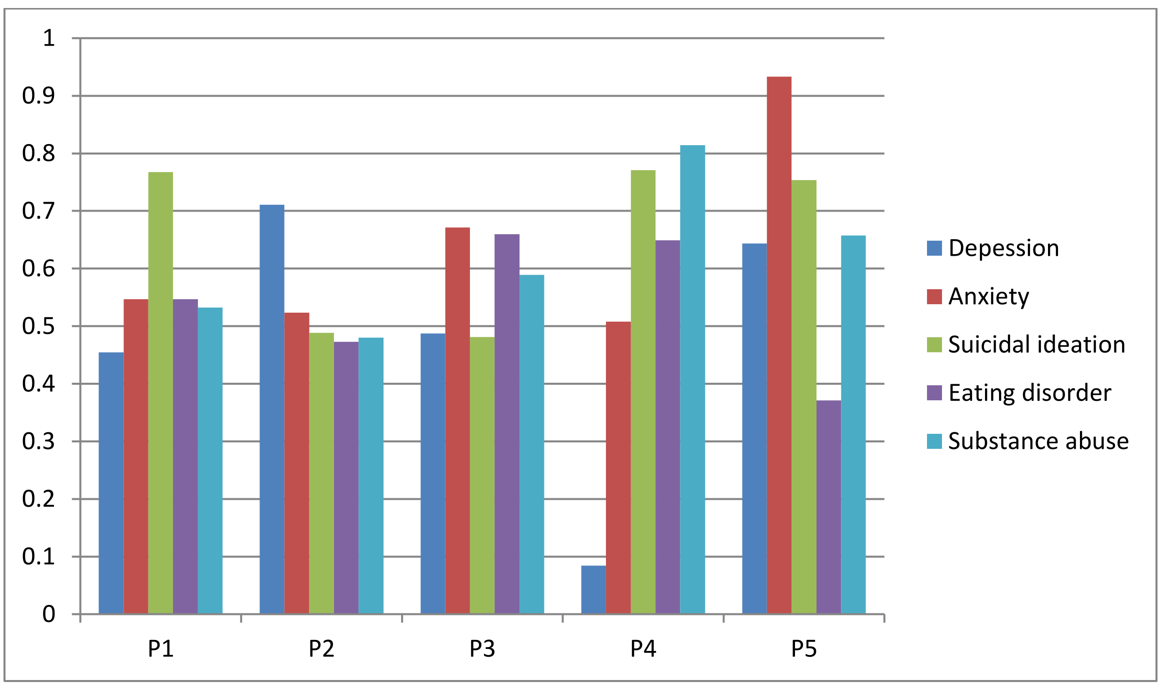
$S_{Mj}(P_4, Ed) = 0.649;$ $S_{Mj}(P_5, Ed) = 0.371.$

$S_{Mj}(P_1, Sa) = 0.5322;$ $S_{Mj}(P_2, Sa) = 0.4800;$ $S_{Mj}(P_3, Sa) = 0.5888;$

$S_{Mj}(P_4, Sa) = 0.814;$ $S_{Mj}(P_5, Sa) = 0.6574.$

Table 4: represents the patient-diseases Intuitionistic fuzzy relation.

$F \to T$	*Depression*	*Anxiety disorder*	*Suicidal ideation*	*Eating disorder*	*Subs tan ce Abuse*
P	0.45456	0.5468	0.7674	0.5470	0.5322
P_2	0.711	0.5234	0.4882	0.4728	0.4800
P_3	0.4872	0.6714	0.4814	0.6594	0.5888
P_4	0.0844	0.5079	0.7708	0.649	0.814
P_5	0.6436	0.9332	0.7534	0.371	0.6574



Graph 3: graphic representation of the patient-diseases Intuitionistic fuzzy relation.

We can forecast which disease five people will have by comparing their similarities to the condition, which increases the likelihood that they will have it. According to the similarity matrix, the first-person experiences suicidal ideation, the second person experiences depression, the third person experiences anxiety, the fourth person engages in drug misuse, and the fifth person experiences anxiety once again. But the most prevalent mental disorder, from which most individuals suffer, is anxiety.

4.2 Construction of Intuitionistic Fuzzy TOPSIS

When making decisions in real life, the information presented is frequently ambiguous and imprecise. IFSs have been found to be an effective technique for very precise decision-making when faced with challenges including ambiguous, hazy, or imprecise information. To improve the efficacy and accuracy of multi-criteria decision making, a number of theories, applications, and approaches based on IFSs have been put out in the literature. In this part, we apply the proposed similarity to issues involving many criteria. In a multi-criteria decision context, TOPSIS is a method for determining which alternative is closest to the positive ideal solution and farthest from the negative ideal solution. We develop an algorithm for Intuitionistic fuzzy TOPSIS to address multi-criteria decision-making issues based on the given similarity measures by extending the TOPSIS idea.

Typically, a set of alternatives is used to define multi-criteria decision-making situations. Among these alternatives, decision-makers have selected the best alternative based on some criteria. Assume that there is a different set.

$H=\{H_1,H_2,H_3,...,H_n\}$ There are n good alternatives to this. Using the above list of alternatives and the set of m criteria, decision-makers should select the best alternative. $K=\left\{K_1,K_2,K_3,...,K_n\right\}$

Suppose that $G=(g_{ij})_{m\times n}$ is decision matrix in the Intuitionistic fuzzy, where $(g_{ij})=(\mu_{ij,}\nu_{ij})$ $i=\left\{1,2,3,...,n\right\}$, $j=\{1,2,3,...,m\}$ is a value assigned to a criterion by the decision-maker, such that $\mu_{ij,}$ shows the extent to which the alternative H_i meets the criteria K_j and ν_{ij} and denotes the extent to which the alternative H_i does not meet the criteria K_j so that

$0\le\mu^2{}_{\hat{A}}(x)+\nu^2{}_{\hat{A}}(x)\le1$ where the function $\mu^2{}_{\hat{A}}(x)\in[0,1]$, $\nu^2{}_{\hat{A}}(x)\in[0,1]$ $i=\left\{1,2,3,...,n\right\}$ and

$j = \{1, 2, 3, ..., m\}$,On the basis of the proposed similarity between IFSs, a novel Intuitionistic fuzzy TOPSIS is proposed. The following is a presentation of the multi-criteria decision-making algorithm using the new Intuitionistic fuzzy TOPSIS:

Step 1: Creating Intuitionistic fuzzy decision matrices and characteristic sets.

$$H_1 = \{(0.1, 0.5), (0.2, 0.4), (0.5, 0.1), (0.1, 0.5), (0.6, 0.2)\};$$

$$H_2 = \{(0.2, 0.6), (0.1, 0.4), (0.4, 0.1), (0.2, 0.6), (0.4, 0.1)\};$$

$$H_3 = \{(0.1, 0.6), (0.3, 0.3), (0.7, 0.1), (0.3, 0.3), (0.5, 0.2)\};$$

$$H_4 = \{(0.2.0, 7), (0.1, 0.5), (0.5, 0.1), (0.2, 0.8), (0.7, 0.3)\};$$

$$H_5 = \{(0.3, 0.6), (0.2, 0.8), (0.6, 0.1), (0.1, 0.4), (0.8, 0.2)\}.$$

Step 1: Decision making matrix:

We indicate the evaluation values of the alternatives in this step**.**, $H = \{H_1, H_2, H_3, ..., H_n\}$

$$H_1 = \{(0.1, 0.5), (0.2, 0.4), (0.5, 0.1), (0.1, 0.5), (0.6, 0.2)\};$$

$$H_2 = \{(0.2, 0.6), (0.1, 0.4), (0.4, 0.1), (0.2, 0.6), (0.4, 0.1)\};$$

$$H_3 = \{(0.1, 0.6), (0.3, 0.3), (0.7, 0.1), (0.3, 0.3), (0.5, 0.2)\};$$

$$H_4 = \{(0.2.0, 7), (0.1, 0.5), (0.5, 0.1), (0.2, 0.8), (0.7, 0.3)\};$$

$$H_5 = \{(0.3, 0.6), (0.2, 0.8), (0.6, 0.1), (0.1, 0.4), (0.8, 0.2)\}.$$

Step 2: $$Wi = \frac{(3\mu_j + \nu_j / 2)}{\sum_{j=1}^{n}(3\mu_j + \nu_j / 2)}$$

$$W_1 = \frac{3.1}{17.45} = 0.17765, \quad W_2 = \frac{2.95}{17.45} = 0.16905, \quad W_3 = \frac{3.6}{17.45} = 0.20530,$$

$$W_4 = \frac{3.7}{17.45} = 0.21489, \quad W_5 = \frac{4.05}{17.45} = 0.23290.$$

Step 3: In this step, we examine the similarities between the Intuitionistic fuzzy positive ideal solution $(IFPIS)B^+$ and negative ideal solution $(IFNIS)B^-$.

Our Positive ideal solution: $B^+ = \{(0.3, 0.5), (0.3, 0.3), (0.7, 0.1), (0.3, 0.3), (0.8, 0.1)\}$

Our Negative ideal solution: $B^- = \{(0.1, 0.7), (0.1, 0.8), (0.4, 0.1), (0.1, 0.8), (0.4, 0.3)$

Step 4: The resemblance between the Intuitionistic fuzzy positive ideal solution $(IFPIS)B^+$ and negative ideal solution $(IFNIS)B^-$ is determined in this step.

$$S_{Mj}(C,D) = \sum_{i=1}^{n} w_i \frac{2min\left(min\left(\mu_C(x_i), \mu_D(x_i)\right), max\left(\nu_C(x_i), \nu_D(x_i)\right)\right)}{min\left(min(\mu_C(x_i), \mu_D(x_i)\right), max\left(\nu_C(x_i), \nu_D((x_i)\right) + max\left(\mu_C(x_i), \mu_D(x_i)\right), min\left(\nu_C(x_i), \nu_D(x_i)\right)} \quad (4)$$

Calculation of similarity measure from $(IFPIS)B^+$ to each alternative by using the above formula as:

$S_{Mj}(H_1, B^+) = 0.1467$; $S_{Mj}(H_2, B^+) = 0.138621$; $S_{Mj}(H_3, B^+) = 0.19928$

$S_{Mj}(H_4, B^+) = 0.197707$; $S_{Mj}(H_5, B^+) = 0.214916$.

Calculation of similarity measure from $(IFNIS)$ B^- to each alternative as;

$S_{Mj}(H_1, B^-) = 0.172924$; $S_{Mj}(H_2, B^-) = 0.163437$; $S_{Mj}(H_3, B^-) = 0.18567$

$S_{Mj}(H_4, B^-) = 0.214899$; $S_{Mj}(H_5, B^-) = 0.20270$

Step 5: Now we calculate relative closeness degree by using $(IFPIS)$ and $(IFNIS)$ as

$$\breve{N}(H_i) = \frac{E^-(H_i)}{E^-(H_i) + E^+(H_i)}$$

$\breve{N}(H_1) = 0.541023$, $\breve{N}(H_2) = 0.541078$, $\breve{N}(H_3) = 0.482322$, $\breve{N}(H_4) = 0.520833$
$\breve{N}(H_5) = 0.485383$

The relative closeness degree is used to rank of alternatives is preferred order.

In Table 2 We've demonstrated how each alternative relates to the Intuitionistic fuzzy positive ideal solution $(IFPIS)$ and Intuitionistic fuzzy negative ideal solution $(IFNIS)$.

Table 5: similarity of alternatives to $(IFPIS)$ and $(IFNIS)$

Similarites	$(IFPIS)$ $S_{Mj}(H_i, B^+)$	$(IFNIS)$ $S_{Mj}(H_i, B^-)$
$S_{Mj}(H_1, B^i)$	0.14670	0.17292
$S_{Mj}(H_2, B^i)$	0.13862	0.16343
$S_{Mj}(H_3, B^i)$	0.19928	0.18567
$S_{Mj}(H_4, B^i)$	0.19770	0.21489
$S_{Mj}(H_5, B^i)$	0.21491	0.20270

The highest relative closeness value indicates that an alternative is closest to $(IFPIS)$ but farthest from $(IFNIS)$. The next table 3 indicates the level of closeness.

Table 6: Closeness degree measure

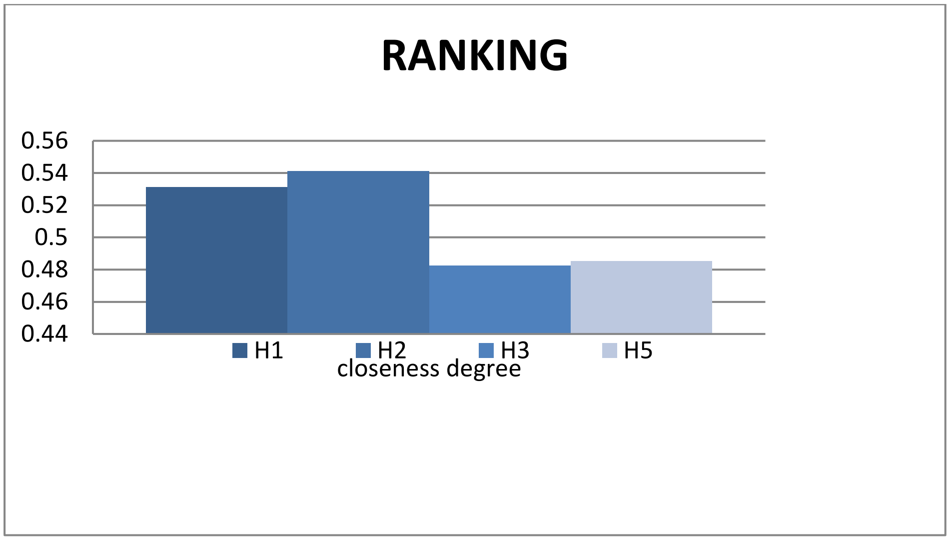
Alternatives	H_1	H_2	H_3	H_4	H_5
Closeness degree	0.521023	0.541078	0.482322	0.520833	0.485383

Ranking of alternatives, the highest degree of closeness will be considered as the best alternatives. We ranked the alternatives accordingly by degree of closeness.

Table 7: represents best alternatives.

Similarity	*Ranking*	*Best Alternative*
S_{Mj}	$H_5 < H_3 < H_4 < H_1 < H_2$	H_2

Graphic representation of best alternatives.



5. CONCLUSION

In this study, a novel and intuitively acceptable method for calculating similarity measures of intuitionistic fuzzy sets is presented (IFSs). We compared the proposed similarity approach of Intuitionistic fuzzy set with the most recent method using a number of instances; the findings indicate that our proposed method is actually more reasonable and intuitive than the existing methods. The proposed similarity measure meets the axiomatic definition of similarity measure, but the existing similarity measure did not. In addition, we applied the proposed similarity measure to multi-criteria decision making TOPSIS and to the diagnosis of mental disorders. In TOPSIS, we use many mental disease symptoms to determine which symptom relates to which disorder. The results indicate that anxiety is the most prevalent mental disorder. Furthermore, female students were shown to be more likely to acquire severe anxiety disorder symptoms (Eisenberg et al., 2007). Our proposed formula is straightforward and could be of great use to those who wish to diagnose their mental disorders.

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