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Technical Note

Soft set based new decision-making method with cardiovascular disease application

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ABSTRACT

A Pythagorean fuzzy set is characterized by values satisfying the condition that the square sum of the degree of membership and degree of non-membership is less than or equal to 1. As a generalized set, Pythagorean fuzzy sets have a close relationship with intuitionistic fuzzy sets. In this study, an algorithm is given that can select patients at risk of developing heart disease based on cardiovascular data. This given algorithm is created with Pythagorean fuzzy soft sets. The new algorithm is offered a medical decision-making method to assist in medical diagnosis. A medical case was examined as a real-life application to see if the proposed method is applicable. The real dataset which is called the Cleveland heart disease dataset has been chosen. In the application, the dataset is arranged as PFSS. In addition, the parameter set was determined and calculations were made in accordance with PFSS. A comparison table was created with the values obtained from these calculations. By choosing the maximum of the values obtained with the score function, the patient with the highest risk of developing heart disease was determined.

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INTRODUCTION

A primary assignment of medicine is to diagnose diseases. However, it is known that diagnosing diseases is not a simple task. Because no matter how much information physicians' have about symptoms, diagnosis of the disease contains uncertainty. When the diagnosis is made on time and closest to accuracy, the patient's health result will be positive. Because clinical decision-making will be tailored to a correct understanding of the patient's health problem.

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The accurate diagnosis and the most effective treatment appropriate for this diagnosis will also positively affect public policy. Thus, extravagance in health payments, which has an important place in public finance, will be avoided, allocated resources will be used accurately, and research and development opportunities will increase.

Increasing options in diagnosis and treatment, diversification of biomedical tools that support clinical applications, common diagnoses in patients cause complexity in health care. Many theories have been developed to reduce this complexity and uncertainty and still continue to be developed. Successful results have been obtained as these theories have been developed and applied, and thus, they have been widely used in the fields of medical diagnosis.

Cardiovascular disease describes a range of conditions that affect the heart. Diseases under the heart disease umbrella include blood vessel diseases, such as coronary artery disease, heart rhythm problems (arrhythmias), and heart defects born with (congenital heart defects), among others. Cardiovascular disease generally refers to conditions that involve narrowed or blocked blood vessels that can lead to a heart attack, chest pain (angina), or stroke. Other heart conditions, such as those that affect your heart's muscle, valves, or rhythm, also are considered forms of heart disease.

Cardiovascular disease is one of the leading causes of death for both women and men. The high number of deaths from cardiovascular disease in the world makes this disease a major concern that needs to be addressed. Identifying cardiovascular diseases is difficult because of diabetes, high blood pressure, high cholesterol, abnormal pulse rate, and many other different risk factors. Recently, modern methods, such as algorithms, have begun to be used to circumvent such constraints and to predict and diagnose heart disease.

Decision-making systems created with the help of algorithms enable the processing of very large data produced in the health sector and the prediction/diagnosis processes to be more effective. The algorithms obtained with the Fuzzy Set Theory, which is the basis of these processes, have positive effects on the decision-making processes of physicians.

The fuzzy sets (FSs) theory [24] brought a paradigmatic change in mathematics. However, in some special cases, the issue of how to set the membership function of the FSs caused problems. To solve these difficulties, Atanassov [2] developed the Intuitionistic fuzzy set (IFS) concept, which is a generalization of FS. Each element in the IFS is expressed by an pair (m,n) satisfying the condition $m + n \leq 1$.

There are many theories like the theory of probability, theory of FSs, theory of IFSs, theory of rough sets, etc. which can be considered as mathematical tools for dealing with uncertain data, obtained in various fields of engineering, physics, computer science, economics, social science, medical science, and of many other diverse fields. However, all these theories have their own particular difficulties in eliminating uncertainties. As a necessary supplement to the existing mathematical tools for handling uncertainty, Molodtsov [14] introduced the theory of soft sets (SSs) as a new mathematical tool to deal with uncertainties while modelling the problems in engineering, physics, computer science, economics, social sciences, and medical sciences. In these various fields, the soft set theory is being used very conveniently due to the absence of any restrictions on the approximate descriptions. Some developments in SSs, FSs, and applications in DM can be found in [1, 9, 10, 11, 12, 13].

Yager [20, 21] offered a new FS called Pythagorean fuzzy set (PFS). PFS attracted the attention of many researchers in a short time. In [23], PF subsets and its relationship with IF subsets were debated and some set operations on PF subsets were defined. In [17], the properties such as boundedness, idempotency, and monotonicity related to the Pythagorean fuzzy aggregation operators are investigated. Further, to solve uncertainty, multiple attribute group, DM problems Pythagorean fuzzy superiority and inferiority ranking method was developed in [17]. Peng et al. [16], defined the PFSS and investigated its properties. Guleria and Bajaj [8] proposed PF soft matrix and its diverse feasible types. Athira et al. [3] have defined new entropy and distance measures for PFSSs. They also studied the applications of PFSSs in decision-making processes and pattern recognition problems. In [4], some new entropy measures are defined for PFSS to calculate the degree of turbidity of the cluster, taking advantage of the fact that PFSS considers the parameterized tool of the PFS family. In this study, a decision-making algorithm is given to solve decision-making problems. Ejegwa [5] presented axiomatic definitions of distance and similarity measures for Pythagorean fuzzy sets, taking into account the three parameters that describe the sets. It is discovered that Hamming and Euclidean distances and similarities fail the metric conditions in the Pythagorean fuzzy set setting whenever the elements of the two Pythagorean fuzzy sets, whose distance and similarity are to be measured, are not equal. Therefore, new measures were needed.

The main feature of the PFS is to relax the condition that the sum of the degree of membership functions is less than one with the square sum of the degree of membership functions is less than one. In the work of Garg [6], under these environments, aggregator operators, namely, Pythagorean fuzzy Einstein weighted averaging, Pythagorean fuzzy Einstein ordered weighted averaging, generalized Pythagorean fuzzy Einstein weighted averaging, and generalized Pythagorean fuzzy Einstein ordered weighted averaging, are proposed. Garg [7] proposed a new correlation coefficient and weighted correlation coefficient formulation to measure the relationship between two PFSs. Kirisci [12] defined the Pythagorean Fuzzy Parametrized Pythagorean Fuzzy Soft Set (Ω-Soft Set) and investigate some properties of the new set. In [13], new parameter reduction methods are given according to Pythagorean fuzzy soft sets to help decision-makers facilitate their decision-making processes. Naeem et al. [15] examined new concepts related to PFSSs. Using the richness of linguistic variables based on Pythagorean fuzzy soft (PFS) information, operations on the properties of PFSSs are presented. In this study, a multi-criteria group decision-making algorithm and its application are given. Peng and Yang [18] extended linguistic Pythagorean fuzzy sets to cubic linguistic Pythagorean fuzzy sets. In [19], Peng and Selvachandran examined the Pythagorean fuzzy sets with an intense and comprehensive overview. In [20], the concept of PFSS was applied to hypergraphs and the concept of Pythagorean fuzzy soft hypergraphs was derived. Yager and Abbasov [22] discussed the relation between Pythagorean membership degrees and complex numbers. In [25], Zhang and Xu propose a score function-based comparison method to identify the Pythagorean fuzzy positive ideal solution and the Pythagorean fuzzy negative ideal solution. Then, they define a distance measure to calculate the distances between each alternative and the Pythagorean fuzzy positive ideal solution as well as the Pythagorean fuzzy negative ideal solution, respectively.

Classical methods cannot be used successfully to solve complex problems in the fields of economics, engineering, and the environment due to various uncertainties specific to these problems. There are three theories for solving these problems: probability theory, fuzzy sets theory, and interval mathematics, which we can consider as mathematical tools for dealing with uncertainties. But all these theories have their own difficulties. Uncertainties cannot be addressed using conventional mathematical tools but can be addressed using a wide variety of existing theories, such as probability theory, (intuitionistic) FS theory, interval mathematical theory, and theory. However, all these theories have their own difficulties. Molodtsov [14] suggested that one reason for these difficulties may be the inadequacy of the theory's parameterization tool. To overcome these difficulties, Molodtsov introduced the concept of soft set(SS) theory as a new mathematical tool for dealing with the difficulties-free uncertainties that plague usual theoretical approaches. Later, Fuzzy Soft Set, Intuitionistic Fuzzy Soft Set, Pythagorean Fuzzy Soft Sets were developed. Since FSS only calculates with the membership function, even if similar results are obtained with similar algorithms, the results obtained in the PFSS method are clearer and stronger. The IFSS uses a membership function and a non-membership function, and the sum of these two functions must be less than or equal to 1. In this case, if the sum of the values is greater than 1, the result cannot be obtained. Calculations with Riesz Mean in the study in [9] were compared with IFSS and gave the same results as IFSS. Therefore, the results of the PFSS were found to be more general and inclusive than the results obtained with the Riesz mean. In the study using trapezoidal fuzzy numbers in the FSS method [11], the operations are more and more difficult than the operations of PFSS.

In this study, an algorithm will be given that will examine cardiovascular data and compare and select the person(s) who suffer from heart disease the most. For the numerical application of this algorithm, one of the most used datasets, the Cleveland Heart Disease dataset from the UCI Repository [26], will be considered. With this algorithm, a new DM method that helps medical diagnosis will be obtained by using PFSSs.

MULTI-CRITERIA DECISOIN MAKING (MCDM)

The analysis of the way people makes decisions (prescriptive theories) or the way people ought to make decisions (normative theories) is perhaps as old as the recorded history of mankind. Of course, not all these analyses were characterized by the rigorous scientific approaches we see in the literature today. Therefore, it is not surprising that the literature in decision-making is humongous and continuously increasing. At the same time, however, the development of the perfect decision-making method for rational real-life decision-making still remains an elusive goal. This contradiction between the extensiveness of the study on this subject and the elusiveness of the final goal of the real-life applicability of the findings constitutes in a way the ultimate decision-making paradox.

MCDM making models that deal with decision-making based on various criteria are a branch of Operations Research. Examine complex problems with characteristics such as MCDM, high uncertainty, conflicting objectives, different forms of information and data, multiple interests, and perspectives; it is an operational evaluation and decision support approach suitable for explaining complex and evolving biophysical and socio-economic systems. MCDM is also a discipline that encompasses mathematics, management, informatics, psychology, social sciences, and economics. Since MCDM methods can be used to solve any problem where an important decision needs to be taken, their applications are expanding even more. These decisions can be tactical or strategic decisions according to the time perspective of the results.

A decision-making mechanism is a human activity in which the human being, as the decision-maker, can hardly escape the effect of multiple conditions that, give shape to what will become the winning decision. In order to reach this winning decision, Multi-Criteria Decision Making (MCDM) has become one of the most important and fastest-growing fields today.

Multi-criteria decision-making (MCDM) is one of the most well-known branches of decision-making. MCDM is divided into multi-objective decision making (MODM) and multi-attribute decision making (MADM). However, very often the terms MADM and MCDM are used to mean the same class of models. MODM studies decision problems in which the decision space is continuous. A typical example is mathematical programming problems with multiple objective functions. Also known as the "vector-maximum" problem. On the other hand, MCDM/MADM concentrates on problems with discrete decision spaces. In these problems, the set of decision alternatives has been predetermined.

An MCDM process is a system, composed of objectives, scenarios, alternatives, criteria, actions, resources, and performance values, and consequently, all of them are usually connected. It is then important when dealing with a scenario for selecting the best alternative amongst many, and all of them subject to criteria, to investigate even summarily if criteria are independent or related between them by direct or indirect links.

Most problems in MCDM refer to the selection of an alternative from a given set and subject to a group of evaluation criteria. Normally, in the set of alternatives, all of them are of the same type (for instance, select the best place to install a car assembly plant, where all alternatives are locations) or selection for purchasing a house (all alternatives are houses), etc. However, in many cases, alternatives belong to different classes and apply to different areas, and this constitutes a complex scenario, although realistic. In this case, the design of the MCDM model is very important. This is a complex task that demands not only a profound knowledge of the scenario under study but also skills to replicate it as close as possible. There is no norm, regulation or directive, as to how to model a scenario. Naturally, each case is different but there is a principle that should always be applied.

METHOD

In this section, a Pythagorean fuzzy soft set-based algorithm is designed for cardiovascular disease diagnosis, which can achieve high accuracy. The Pythagorean fuzzy set-based algorithm consists of eight steps.

As an intuitionistic fuzzy set(IFS), characterized by the degrees of membership and non-membership, the satisfaction of the particular alternative with respect to the criteria, such as their sum, is equal to or less than 1. However, there may be a situation where the decision-maker may provide the degree of membership and non-membership of a particular attribute in such a way that their sum is greater than 1. To overcome this shortcoming, Yager introduced a concept of the PFS, generalization of the IFS, under the restriction that the square sum of its membership degrees is less than or equal to 1. Since PFSs' appearance, several researchers have paid attention to multi-criteria decision-making (MCDM) problems under the PF environment.

Let's U denote the initial universe. An Pythagorean fuzzy set (PFS) C in U is given by $C = \{(x, m_C(x), n_C(x)) : x \in U\}$, where $m_C(x): U \rightarrow [0,1]$ denotes the degree of membership and $n_C(x): U \rightarrow [0,1]$ denotes the degree of non-membership of the element $x \in U$ to the set C with the condition that $0 \leq [m_C(x)]^2 + [n_C(x)]^2 \leq 1$. The degree of indeterminacy $p_C = \sqrt{1 - [m_C(x)]^2 - [n_C(x)]^2}$ [20].

Let the initial universe set and parameters set denote with U, P respectively. Let $\rho(U)$ denotes the set of all PFSs over U. Let $C \subseteq P$. F_C is called Pythagorean fuzzy soft set (PFSS) on U, if F is mapping given by $F_C: C \rightarrow \rho(U)$ [16].

Let Pythagorean fuzzy numbers (PFNs) are denoted by $N = (m_N, n_N)$. Choose three PFNs $N = (m,n)$, $N_1 = (m_{N1}, n_{N1})$, $N_2 = (m_{N2}, n_{N2})$. We can give some basic operations as follows:

$$N_1 \oplus N_2 = \left(\overset{\bar{N}=(n,m);}{\sqrt{m_1^2 + m_2^2 - m_1^2 \cdot m_2^2}, \; n_1 n_2} \right),$$

$$N_1 \otimes N_2 = \left(m_1 m_2, \; \sqrt{n_1^2 + n_2^2 - n_1^2 \cdot n_2^2} \right),$$

$$N_1 \wedge N_2 = \left(\min\{m_1, m_2\}, \max\{n_1, n_2\} \right),$$

$$N_1 \vee N_2 = \left(\max\{m_1, m_2\}, \min\{n_1, n_2\} \right),$$

$$\alpha N = \left(\sqrt{1 - (1 - m^2)^\alpha}, \; n^\alpha \right),$$

$$N^\alpha = \left(m^a, \sqrt{1 - (1 - n^2)^\alpha} \right).$$

Firstly, we will give PFSS method:

Choose a set of k objects as $U = \{p_1, p_2, \ldots, p_k\}$, and a set of parameters $\{A(1), A(2), \ldots A(i)\}$. Each parameter set $A(i)$ represent the ith class of parameters and the elements of $A(i)$ indicates a certain property set. Assumed that the property sets can be shown as FSs. Let F_C, F_D be the PFSSs on U [16].

Table 1. Attributes of Cleveland dataset

Attributes	Full name
a_1	Age in years
a_2	Chest pain type
a_3	Resting blood pressure (in mm Hg)
a_4	Serum cholesterol in mg\dl
a_5	Fasting blood sugar >120 mg\dl
a_6	Resting electrocardiographic results
a_7	Maximum heart rate achieved
a_8	ST depression induced by exercise relative to rest
a_9	The slope of the peak exercise ST segment
a_{10}	Number of major vessels (0-3) colored by flourosopy
a_{11}	3 normal; 6 fixed defect; 7 reversible defect

Table 2. The PFSS F_C

	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8	a_9	a_{10}	a_{11}
p_1	(0.9,0.0)	(0.2,0.5)	(0.5,0.4)	(0.3,0.7)	(0.1,0.9)	(0.1,0.8)	(0.6,0.3)	(0.3,0.5)	(0.7,0.2)	(0.1,0.6)	(0.5,0.4)
p_2	(0.9,0.1)	(0.8,0.0)	(0.6,0.2)	(0.4,0.5)	(0.1,0.7)	(0.8,0.1)	(0.4,0.3)	(0.2,0.5)	(0.5,0.5)	(0.8,0.1)	(0.1,0.6)
p_{24}	(0.7,0.2)	(0.2,0.6)	(0.4,0.4)	(0.5,0.3)	(0.1,0.6)	(0.0,0.9)	(0.2,0.7)	(0.3,0.6)	(0.7,0.1)	(0.6,0.5)	(0.9,0.1)
p_{25}	(0.1,0.8)	(0.8,0.0)	(0.5,0.4)	(0.6,0.3)	(0.1,0.7)	(0.9,0.1)	(0.3,0.5)	(0.5,0.4)	(0.5,0.5)	(0.6,0.3)	(0.9,0.1)
p_{75}	(0.5,0.5)	(0.1,0.8)	(0.2,0.5)	(0.4,0.3)	(0.1,0.5)	(0.5,0.5)	(0.8,0.2)	(0.0,0.7)	(0.1,0.7)	(0.5,0.2)	(0.6,0.1)
p_{303}	(0.5,0.4)	(0.6,0.2)	(0.5,0.4)	(0.3,0.6)	(0.1,0.5)	(0.1,0.5)	(0.6,0.2)	(0.0,0.8)	(0.1,0.5)	(0.4,0.4)	(0.2,0.6)

Table 3. The PFSS F_D

	1	2	3	4	0
p_1	(0.3,0.6)	(0.2,0.7)	(0.1,0.7)	(0.0,0.9)	(0.9,0.0)
p_2	(0.8,0.0)	(0.9,0.1)	(0.8,0.1)	(0.5,0.4)	(0.0,0.9)
p_{24}	(0.7,0.1)	(0.8,0.1)	(0.9,0.2)	(0.8,0.1)	(0.0,0.8)
p_{25}	(0.3,0.6)	(0.5,0.5)	(0.8,0.1)	(0.9,0.1)	(0.0,0.8)
p_{75}	(0.9,0.3)	(0.8,0.3)	(0.4,0.6)	(0.2,0.7)	(0.5,0.5)
p_{303}	(0.2,0.6)	(0.1,0.7)	(0.1,0.6)	(0.0,0.8)	(0.9,0.1)

Table 4. The PFSS F_K

	1	2	3	4	0
p_1	(0.5,0.6)	(0.3,0.6)	(0.2,0.7)	(0.1,0.8)	(0.2,0.9)
p_2	(0.6,0.2)	(0.3,0.6)	(0.1,0.7)	(0.0,0.6)	(0.8,0.1)
p_{24}	(0.5,0.3)	(0.6,0.2)	(0.8,0.4)	(0.9,0.2)	(0.0,0.9)
p_{25}	(0.4,0.5)	(0.5,0.6)	(0.6,0.3)	(0.7,0.4)	(0.0,0.9)
p_{75}	(0.3,0.6)	(0.8,0.2)	(0.5,0.4)	(0.3,0.8)	(0.5,0.4)
p_{303}	(0.3,0.6)	(0.2,0.7)	(0.2,0.5)	(0.1,0.9)	(0.8,0.1)

i. The operation $F_C \wedge F_D$ is called 'AND' operator on F_C, F_D such that $F_C \wedge F_D = F(G \times H) = \{\min(m_C, m_H), \max(n_C, n_H)\}$.

ii. The operation $F_C \vee F_D$ is called 'OR' operator on F_C, F_D such that $F_C \vee F_D = F(G \times H) = \{\max(m_C, m_H), \min(n_C, n_H)\}$.

A square table with equal row numbers and column numbers is called a Comparison Table. This table contains $\{p_1, p_2, \ldots, p_n\}$ object names in both rows and columns. The entries in Comparison Table are denoted by c_{ij}, $(i,j = 1, \ldots, n)$. These entries are defined as is the number of parameters for which the membership value of p_i greater than or equal to the membership value of p_j and non-membership values of p_i less than or equal to the non-membership value of p_j.

If we take the number of parameters in PFSS as k, then it is clear that $0 \le c_{ij} \le k$, for all i,j. Further $c_{ii} = k$. From here it is understood that c_{ij} is an integer number as a numerical measure.

The formula $r_i = \sum_{j=1}^{n} c_{ij}$ calculates the row sum for an object p_i. In this calculations, r_i indicates the total number of parameters in which p_i dominates all the members of U.

In the same way, the formula $t_j = \sum_{i=1}^{n} c_{ij}$ yields the column sum for an object p_j. In this summation, the integer t_j indicates the total number of parameters in which p_j is dominated by all the members on U.

The formula $S_i = r_i^2 - t_j^2$ give the score of an object p_i.

Now let's give information about the dataset:

Input variables are taken from Cleveland dataset [26] This data set contains 303 patients, 11 attributes and 5 outcomes.

This database contains 76 attributes. However, it is understood that 14 of these attributes can be used. The outcomes are given as degree of disease. It is integer valued from 0 (no presence) to 4. Tests with the Cleveland database have intensively on simply attempting to distinguish presence (values 1,2,3,4) from absence (value 0).

For simplify of operations, some patients can be selected instead of all patients from the Cleveland dataset. Let's choose patient sets $U = \{p_1, p_2, p_{24}, p_{25}, p_{75}, p_{303}\}$ from the Cleveland dateset.

The attributes of Cleveland dataset are given in Table 1. The outcomes are disease degrees as 1,2,3,4 and 0 (absence).

According to the membership function, the age attribute is taken into account as follows: For age in years' attribute, the values of membership function can be given as 0–20 (0.0–0.2), 21–40(0.3–0.5), 41–60 (0.6–0.8); 61 + (0.9–1.0) from the dataset. In this dataset, the attributes trestbps, chol, thalach, oldpeak are measured as lowest 94.0 highest 200.0; lowest 126.0 highest 564.0; lowest 71 highest 195; lowest 0.0 highest 5.6, respectively. We will give values between 0.0 and 1.0 to these measurements.

Algorithm

i. Input the PFSSs F_C, F_D and F_K.

ii. Input the parameter set P obtained as a result of observations.

iii. Compute the corresponding PFSSs $F_C \wedge F_D = F_M$ from the PFSSs F_C, F_D.

iv. Calculate the corresponding resultant PFSS $F_K \wedge F_M = F_S$.

Table 5. The resultant PFSS F_M

	$e_{1,1}$	$e_{1,5}$	$e_{2,3}$	$e_{3,4}$	$e_{4,2}$	$e_{5,3}$	$e_{7,2}$	$e_{9,5}$	$e_{10,1}$	$e_{11,3}$
p_1	(0.3,0.6)	(0.9,0.0)	(0.1,0.7)	(0.0,0.9)	(0.2,0.7)	(0.1,0.9)	(0.2,0.7)	(0.7,0.2)	(0.1,0.6)	(0.1,0.6)
p_2	(0.8,0.1)	(0.0,0.9)	(0.8,0.1)	(0.5,0.4)	(0.4,0.5)	(0.1,0.7)	(0.4,0.3)	(0.0,0.9)	(0.8,0.1)	(0.1,0.6)
p_{24}	(0.7,0.2)	(0.0,0.8)	(0.2,0.6)	(0.4,0.4)	(0.5,0.3)	(0.1,0.6)	(0.2,0.7)	(0.0,0.8)	(0.6,0.5)	(0.9,0.2)
p_{25}	(0.1,0.8)	(0.0,0.8)	(0.8,0.1)	(0.5,0.4)	(0.5,0.5)	(0.1,0.7)	(0.3,0.5)	(0.0,0.8)	(0.3,0.6)	(0.8,0.1)
p_{75}	(0.5,0.5)	(0.5,0.5)	(0.1,0.8)	(0.2,0.7)	(0.4,0.3)	(0.1,0.6)	(0.8,0.3)	(0.1,0.7)	(0.5,0.3)	(0.4,0.6)
p_{303}	(0.2,0.6)	(0.5,0.4)	(0.1,0.6)	(0.0,0.8)	(0.1,0.7)	(0.1,0.8)	(0.1,0.7)	(0.1,0.5)	(0.2,0.6)	(0.1,0.6)

Table 6. The resultant PFSS F_R

	$e_{1,1} \wedge c_1$	$e_{1,5} \wedge c_3$	$e_{2,3} \wedge c_4$	$e_{3,4} \wedge c_2$	$e_{4,2} \wedge c_5$	$e_{5,3} \wedge c_1$	$e_{7,2} \wedge c_3$	$e_{9,5} \wedge c_2$	$e_{10,1} \wedge c_4$	$e_{11,3} \wedge c_1$
p_1	(0.3,0.6)	(0.2,0.7)	(0.1,0.8)	(0.0,0.9)	(0.2,0.9)	(0.1,0.9)	(0.2,0.7)	(0.1,0.6)	(0.1,0.8)	(0.1,0.7)
p_2	(0.6,0.2)	(0.0,0.9)	(0.0,0.6)	(0.3,0.6)	(0.4,0.5)	(0.1,0.7)	(0.1,0.7)	(0.0,0.9)	(0.0,0.6)	(0.1,0.6)
p_{24}	(0.5,0.3)	(0.0,0.8)	(0.2,0.6)	(0.4,0.5)	(0.0,0.9)	(0.1,0.6)	(0.2,0.7)	(0.0,0.8)	(0.6,0.5)	(0.5,0.3)
p_{25}	(0.1,0.8)	(0.0,0.8)	(0.7,0.4)	(0.5,0.6)	(0.0,0.9)	(0.1,0.7)	(0.3,0.5)	(0.0,0.8)	(0.3,0.6)	(0.4,0.5)
p_{75}	(0.5,0.5)	(0.5,0.5)	(0.1,0.8)	(0.2,0.7)	(0.4,0.4)	(0.1,0.6)	(0.5,0.4)	(0.1,0.7)	(0.3,0.8)	(0.4,0.6)
p_{303}	(0.2,0.6)	(0.2,0.5)	(0.1,0.9)	(0.0,0.8)	(0.1,0.7)	(0.1,0.8)	(0.1,0.7)	(0.1,0.7)	(0.1,0.9)	(0.1,0.6)

Table 7. Comparison Table

	p_1	p_2	p_{24}	p_{25}	p_{75}	p_{303}
p_1	10	3	4	3	2	5
p_2	5	10	2	3	2	6
p_{24}	7	8	10	7	6	7
p_{25}	5	8	6	10	4	6
p_{75}	9	6	5	6	10	10
p_{303}	4	4	3	4	1	10

Table 8. r_i, t_i, S_i

	r_i	t_i	S_i
p_1	28	40	–816
p_2	28	39	–737
p_{24}	45	30	1125
p_{25}	39	34	365
p_{75}	46	25	1491
p_{303}	26	44	– 1260

v. Set up the Comparison Table of PFSS F_R and compute r_i, t_i for p_i for all *i*.

vi. Compute the score of p_i for all *i*.

vii. If the obtain value of S_i is maximum ($S_k = max_i S_i$), then signify that decision is S_k.

viii. If k has more than one value then any one of p_k may be chosen.

APPLICATION

Heart disease is one of the biggest causes of morbidity and mortality among the population of the world. Prediction of cardiovascular disease is regarded as one of the most important subjects in the section of clinical data analysis. The amount of data in the healthcare industry is huge. Algorithms for data processing transform the vast collection of raw health data into information that can help make informed decisions and predictions.

First, the PFSS tables are created and the parameter set is set up. In the next step, PFSSs and resultant PFSS are calculated with the AND operator. Score values are obtained by creating a Comparison table. Finally, the maximum of the obtained score values is selected. The Cleveland dataset will be used in the application to be made for the new algorithm.

The PFSS F_C is defined with patients and attributes. The PFSS F_D is obtained from the measurements of Cleveland dataset. In the PFSS F_K, there are predicted values of patients and disease degrees.

Take the PFSSs F_C, F_D in Table 2 and Table 3, respectively and carry out "F_C *AND* F_D" in form e_{ij}, where $e_{ij} = a_i \wedge b_j$. Then, we will have 11 × 5 = 55 parameters of the form e_{ij}, (i = 1, 2, …, 11; j = 1,2,3,4,5). For example, let the PFSS for the parameters

$$G = \{e_{1,1}, e_{1,5}, e_{2,3}, e_{2,4}, e_{4,2}, e_{5,3}, e_{7,2}, e_{9,5}, e_{10,1}, e_{11,3}\}.$$

Then, the resultant PFSS for the PFSSs F_C, F_G will be F_R (Table 5).

Take the PFSSs F_C, F_D, F_K, in Table 2,3,4, respectively. Consider that

$$E = \{e_{1,1} \wedge c_1,\ e_{1,5} \wedge c_5,\ e_{2,3} \wedge c_2,\ e_{3,4} \wedge c_4,\ e_{4,2} \wedge c_3,\ e_{5,3} \wedge c_2,\ e_{7,2} \wedge c_5,\ e_{9,5} \wedge c_1,\ e_{10,1} \wedge c_3,\ e_{11,3} \wedge c_2\}.$$

The tabular representation of resultant PFSS F_K is depicted Table 6.

The Comparison Table of the above resultant PFSS is as Table 7. Later on compute the row-sum (r_i), column-sum (t_i), and the score (S_i) for each p_i, as Table 8.

Now, we construct the tables for medical decision-making by algorithm in previous section:

From the Table 8, it is clear that the maximum score is 1491 and p_{75} has the maximum score. Therefore, we can decide the accuracy of selection of p_{75}.

DISCUSSON

The attributes given in Table 1 were first converted to PFNs. The PFNs in Table 2 shows the relationship between patients and disease characteristics. In other words, values related to cardiovascular disease parameters in selected patients are shown in Table 2. For example, for attribute a_1, patient 2's values were (0.9, 0.1) while patient 25's values were (0.1, 0.8).

In Table 3, the disease degrees of the patients are shown as PFN. For example, Patient 1's state of 4th-degree disease was determined as (0.0, 0.9), while the state of not being sick was determined as (0.9, 0.0). In other words, it can be thought that patient 1 is not sick by looking at these values.

The relationship between 11 attributes and 5 disease degrees is established with e_{ij} values. The AND operator is used for this relationship. The e_{ij} values in this example are 55. The table obtained here is the resultant PFSS F_M and these values are seen in Table 5.

Since it would take a long time to process all the values in Table 5 and would take up a lot of space in the study, some values were selected in a sample G set. The resultant PFSS F_R was obtained by using the AND operator between the values of the F_C and F_G sets. These values are shown in Table 6.

The Comparison Table of the above resultant PFSS is as Table 7. Later on compute the row-sum (r_i), column-sum (t_i), and the score (S_i) for each p_i, as Table 8. From the Table 8, it is clear that the maximum score is 1491 and p_{75} has the maximum score. Therefore, we can decide the accuracy of selection of p_{75}.

CONCLUSION

Since the emergence of IFS [2], it has received a lot of attention in field of science and technology. Unlike FS, IFS does not only have a membership function but also has a non-membership function. The sum of these functions is less than or equal to 1. Having two functions and having totals less than or equal to 1 makes IFS stronger and more decisive than FS. However, in some real-life situations, the total of membership and non-membership functions may be greater than 1 and this creates difficulties in solving problem. That is, IFS fails to cope with such a situation. For this reason, PFS, initiated by Yager to deal with uncertainty, has entered the literature as a very effective tool. Problems that cannot be solved in IFS are more easily solved with PFS and the necessary modelling can be made easier. Therefore, it is claimed that PFS, which is frequently used in the literature about decision-making problems, is a superior model. IFS is PFS, but the opposite does not have to be true.

The concept of PFSS has been defined by Peng et al [18]. This new definition adds the generalization parameter to the pool of PFNs and extends PFS to PFSS. The concept of PFSS, which emerged from PFS, functions to evaluate the information obtained with a parameter that reflects the views of an expert. It is important that the uncertainty associated with an observer be verified by an expert in the choice of degree of membership, and this is the main motivation for developing the PFSS concept. That is, the Pythagorean fuzzy soft sets are generalized by introducing the generalization parameter given by an expert to validate the original Pythagorean fuzzy values. The role of the expert is to refine PFNs with his domain-specific knowledge. It may be noted that information of any sort often gets misinterpreted during its presentation. This usually happens as the presenter has no domain-specific knowledge or lacks the standard terminologies and this is sought to be corrected by the proposed PFSS. An expert can be viewed as a domain professional having years of experience. The expert's opinion indicates the credibility of the evaluation of the alternative by the experts. This opinion coming from the expert constitutes the generalization parameter. The severity of symptoms as reported by the patients in the linguistic form as membership grades can be used in the PFSS.

In this study, PFSS, resultant PFSS, entries of Comparison Table, and score measures were given for PFSSs according to the PFNs. In decision-making processes, the criteria that determine the decisions are not of equal importance. Therefore, the properties are determined as PFN and shown in the tables.

In this paper, a new decision-making method is given using the PFSS. The proposed algorithm for the decision-making process has been successfully implemented with the help of a numerical example. The method proposed by the study can be easily used to solve MCDM problems where data describing the performance of alternatives are characterized by PF values.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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