Spectrum of Engineering and Management Sciences, Volume 1, Issue 1 (2023) 73-82

Spectrum of Engineering and Management Sciences

Journal homepage: www.sems-journal.org
ISSN: 3009-3309

Enhancing Diabetes Diagnosis through an Intuitionistic Fuzzy Soft Matrices-Based Algorithm

Muhammad Naveed Jafar[1], Kainat Muniba[2], Muhammad Saqlain[3*]

[1] Department of Mathematics, University of Management and Technology, Lahore, Pakistan
[2] Department of Environmental Sciences and Policy, Lahore School of Economics, Lahore, Pakistan
[3] Departments of Mathematics, Faculty of Science, King Mongkut's University of Technology Thonburi (KMUTT), Bangkok 10140, Thailand

ARTICLE INFO

Article history:
Received 8 September 2023
Received in revised form 5 October 2023
Accepted 16 October 2023
Published 22 October 2023

Keywords:
Decision-Making; Soft Set; IFS; IFSMs; Complement of IFSMs; Product of the IFSM

ABSTRACT

The diagnosis of Type-1 diabetes is a challenging and sophisticated procedure for medical experts. The complexity of this condition necessitates the use of sophisticated decision-making tools, and in this setting, intuitionistic soft set theory and its accompanying matrices prove to be invaluable resources. Our suggested technique uses intuitionistic soft matrices to solve challenging multi-criteria decision-making issues, opening a promising new direction for improving the precision of diabetes diagnosis. Diabetes requires careful evaluation and assessment since it is characterized by several illnesses that interfere with the body's capacity to control blood plasma glucose levels. Our main goal is to use intuitionistic fuzzy soft matrices to thoroughly examine diabetic patients in the decision-making domain. By giving medical professionals more accurate tools to treat this pervasive and difficult health issue, this novel strategy has the potential to revolutionize the diagnosis and management of diabetes.

1. Introduction

Multiple-criteria decision-making (MCDM) procedures have become essential resources in the field of medical diagnosis, especially when dealing with ambiguity. Healthcare workers frequently encounter complex instances where it is necessary to consider several different elements to make a proper diagnosis. The integration of several variables, including patient symptoms, medical history, results of diagnostic tests, and clinical competence, into a thorough decision-making framework is made possible by MCDM approaches. Furthermore, doubt is a natural part of medical practice because not all symptoms or test results are clear-cut. With the use of MCDM techniques, this uncertainty may be modeled and managed, giving doctors a methodical and logical way to weigh the risks of various diagnostic alternatives. Many researchers have used mathematical techniques to streamline complicated issues and get around potential challenges over time. Even while traditional

* *Corresponding author.*
E-mail address: muhammad.saql@kmutt.ac.th

https://doi.org/10.31181/sems1120238u

numerical methods have frequently been successful, there are some situations when they fail to offer workable answers. These situations frequently entail dealing with ambiguity, demanding methods beyond the realm of classical mathematics. Numerous theoretical frameworks, such as probability theory, fuzzy soft sets, and interval mathematics, have been proposed to handle such uncertainties and other difficulties. These frameworks were created specially to deal with these difficult and uncertain circumstances. By incorporating MCDM into medical diagnosis, healthcare practitioners can enhance the precision and reliability of their assessments, ultimately leading to improved patient care and outcomes.

Zadeh [1] was the first to establish the idea of a fuzzy set to deal with uncertain, vague, and imprecise environments. Then many applications involving uncertainty make extensive use of fuzzy sets. There are still some cases when a fuzzy set cannot be used, hence the idea of the interval-valued fuzzy set was introduced to analyze these circumstances [2]. In 1982, Pawlak [3] presented a rough set theory which is the centrality of approach to modeling unclearness. In 1986, Antanassov [4] introduced a new concept known as intuitionistic fuzzy set theory (IFS). In this theory, he discussed a non-membership value along with the membership function. The value of IFS is considered in the interval [0, 1]. Correlation coefficients are very important in decision-making. They were proposed for IFSs by [5]. In the year 1999, Moldstov [6] introduced a soft set like a genetic mathematical method for modeling uncertainty. In 2003, Maji [7] further studied soft set theory and introduced a wonderful idea by combining soft set and fuzzy set. He introduced a fuzzy soft set and used that concept in MCDM problems. Deli [8] introduced the idea of intuitionistic fuzzy soft set (IFSS) theory. The interval value is lying between [0, 1]. Maji [9] presented more work on it. Agarwal [10] presented the generalization on IFSS. Many authors have proposed many research papers about different diseases by using fuzzy and intuitionistic soft sets such as [11–12].

Diabetes is a fatal disease that has been affecting more people day by day. This disease is common in all age groups and affects both males and females in approximately equal ratio. Diabetes mellitus has increased tremendously, not only in urban areas but also in rural areas of the whole world. The presence of this disease is prominent in countries of South Asia and the Middle East. In Pakistan, there’s a major population affected by diabetes. According to certain reputable sources, the percentage of affected males by diabetes in Pakistan is 11.2% and females are 9.19% from 1995 to 2014. By using intuitionistic fuzzy soft matrices (IFSMs), diagnosis can be applied to the patient under observation assimilating whether he has diabetes type-1 or type-2. For better and more accurate results, IFSMs prove useful in medical diagnosis.

Diabetes consists of an amalgamation of diseases due to which the afflicted body cannot process the amount of glucose in the blood plasma. The pancreas, an organ located beside the stomach, releases necessary enzymes that assist in digesting the sugar molecules. Type-1 positive patients are not capable of utilizing insulin properly whereas type-2 positive patients are not capable of producing sufficient insulin to begin with. Type-1 In this case, the pancreas proceeds with the secretion of insulin but the ability to utilize the insulin is partially or completely lost. In other words, the body is insulin-resistant. This results in the body trying to secrete the insulin further. The consequences become much worse as an insulin-resistant body cannot keep up with the high requirements and the patient becomes type-2 positive. Type-1 patients are often discovered in their early years (0-20). It was addressed as Juvenile onset diabetes. An older fellow can contract type-1 when subjected to alcohol abuse, other diseases, or failure of pancreatic cells. Type-2 is also addressed as adult-onset diabetes. The production of insulin is minimal or nonexistent within these patients. Not so surprisingly, about 90% of these patients are type-2 positive. This is majorly common in adults who are above 40 years of age. Type-2 diabetes is managed with a balanced diet, exercise, yoga, and meditation. Most type-2 patients rely on insulin to control their blood. Khan et al. [13] used the IFSS in decision support systems. Several researchers proposed a novel method that applied IFSS to solve decision-making problems [14–15]. They used this approach to study agriculture sciences, used the Sanchez method to diagnose patients, and created an algorithm.

The concept of IFSM was proposed by [16]. Growing interest has been shown in the creation and use of various soft computing models and decision-making processes in recent years. The IFSS theory, which offers a framework for dealing with uncertainty in decision-making processes, was introduced by Aman and Karataş [17]. Jafar et al. [18] used trapezoidal fuzzy numbers to implement Sanchez's strategy for disease identification, demonstrating the potential of soft computing methods in the realm of medical diagnosis. Meo et al.'s [19] analysis of type-2 diabetes mellitus prevalence and forecast in Pakistan illustrated the usefulness of soft computing techniques in healthcare administration. Additionally, Jafar et al. [20] investigated the usage of neutrosophic soft matrices for new technology applications in agriculture using scoring functions. These studies demonstrate the adaptability of soft computing models across a range of industries, including agriculture and healthcare. Additionally, uncertain linguistic fuzzy soft sets, which have found use in group decision-making scenarios, were introduced to the literature by Tao et al. [22] and Vijayabalaji and Ramesh [23]. Wang et al. [24] introduced multi-attribute group decision-making approaches based on q-rung orthopair fuzzy language sets to further expand the application of soft computing to group decision-making processes. Wu et al.'s [25] innovative MCDM approach expanded the use of soft computing in decision-making by incorporating heterogeneous verbal expressions. Additionally, Saqlain et al. [26–30] expanded on the idea of neutrosophic hypersoft sets by providing novel operators and decision-making similarity metrics. Interval-valued picture fuzzy uncertain linguistic Dombi operators were introduced by Jana and Pal [31], extending the soft computing applications to industrial fund selection. In the area of sustainable hydrogen production, Saqlain [32] also used VIKOR and intuitionistic hypersoft sets. Soft computing's involvement in healthcare was expanded by [33] with the introduction of an intuitionistic fuzzy soft matrix-based method for medical decision support systems. By introducing diverse extensions and applications in various fields, Majumdar and Samanta [34], Ali et al. [35], Vijayabalaji and Ramesh [36], and Aiwu and Hongjun [37] made major contributions to the field of soft sets. Uncertain linguistic fuzzy soft sets were finally introduced by Tao et al. [38], contributing to the corpus of knowledge on the use of soft computing techniques in group decision-making.

Collectively, these works show how soft computing models may manage ambiguity and complexity in decision-making processes across a variety of disciplines with broad-reaching effects. The motivation behind the study is researchers ignore the factor of non-existence. We consider that scenario when something is in an existing position then we must discuss its non-existence situation about existence. Also, a useful technique in healthcare decision-making is MCDM, particularly when deciding on treatments for long-term diseases like diabetes. MCDM aids patients and physicians in making educated decisions that cater to the individual's requirements and preferences by methodically analyzing and weighting multiple variables, ultimately resulting in better health outcomes and enhanced quality of life. Finally, we proposed the complement of matrices to deal with that situation and propose an algorithm to solve such kinds of problems. The aim of the study is the most efficient and refined results than existing techniques;

2. Intuitionistic Fuzzy Soft Matrices

Definition 1: Let a universal set is $\dot{\tilde{U}}$ and attributes set is $\dot{\tilde{D}}$. Then, IFSMs is $\left(\dot{\tilde{f}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ over $\dot{\tilde{U}}$. The function $\dot{\tilde{U}} \times \dot{\tilde{D}}$ defined as $\dot{\tilde{X}}_{\dot{\tilde{A}}} = \left\{\left(\dot{\tilde{h}}, \dot{\tilde{e}}\right), \dot{\tilde{e}} \in \dot{\tilde{A}}, \dot{\tilde{h}} \in \dot{\tilde{f}}_{\dot{\tilde{A}}}(\dot{\tilde{e}})\right\}$ is called relation form; i.e. $\left(\dot{\tilde{f}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$. The membership function can be written as $\dot{\tilde{\mu}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}: \dot{\tilde{U}} \times \dot{\tilde{D}} \to [0,1]$, where $\dot{\tilde{\mu}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}: \left(\dot{\tilde{h}}, \dot{\tilde{e}}\right) \in [0,1]$ is membership value and the non-membership function is written as $\dot{\tilde{v}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}: \dot{\tilde{U}} \times \dot{\tilde{D}} \rightarrow [0, 1]$ where $\dot{\tilde{v}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}: \left(\dot{\tilde{h}}, \dot{\tilde{e}}\right) \in [0, 1]$ is non-membership value; i.e. $\dot{\tilde{h}} \in \dot{\tilde{\mu}}$ and $\dot{\tilde{e}} \in \dot{\tilde{D}}$. If $(\dot{\tilde{\mu}}_{ij}, \dot{\tilde{v}}_{ij}) = \left(\dot{\tilde{\mu}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}\left(\dot{\tilde{h}}_i, \dot{\tilde{e}}_j\right), \dot{\tilde{v}}_{\dot{\tilde{X}}_{\dot{\tilde{A}}}}\left(\dot{\tilde{h}}_i, \dot{\tilde{e}}_j\right)\right)$, then the matrix can be defined as:

$$[(\dot{\tilde{\mu}}_{ij}, \dot{\tilde{v}}_{ij})]_{m\times n} = \begin{bmatrix} (\dot{\tilde{\mu}}_{11}, \dot{\tilde{v}}_{11}) & (\dot{\tilde{\mu}}_{12}, \dot{\tilde{v}}_{12}) & \dots & (\dot{\tilde{\mu}}_{1n}, \dot{\tilde{v}}_{1n}) \\ (\dot{\tilde{\mu}}_{21}, \dot{\tilde{v}}_{21}) & (\dot{\tilde{\mu}}_{22}, \dot{\tilde{v}}_{22}) & \dots & (\dot{\tilde{\mu}}_{2n}, \dot{\tilde{v}}_{2n}) \\ . & . & & . \\ . & . & & . \\ . & . & & . \\ (\dot{\tilde{\mu}}_{m1}, \dot{\tilde{v}}_{m1}) & (\dot{\tilde{\mu}}_{m2}, \dot{\tilde{v}}_{m2}) & \dots & (\dot{\tilde{\mu}}_{mn}, \dot{\tilde{v}}_{mn}) \end{bmatrix}, \tag{1}$$

where $[(\dot{\tilde{\mu}}_{ij}, \dot{\tilde{v}}_{ij})]_{m\times n}$ is known as IFSMs of IFSS $\left(\dot{\tilde{f}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ defined over $\dot{\tilde{U}}$.

Example 1: Let the universal set is $\dot{\tilde{U}} = \left\{\dot{\tilde{h}}_1, \dot{\tilde{h}}_2, \dot{\tilde{h}}_3, \dot{\tilde{h}}_4\right\}$ and attribute set is $\dot{\tilde{D}} = \{\dot{\tilde{p}}_1, \dot{\tilde{p}}_2, \dot{\tilde{p}}_3\}$. If $\dot{\tilde{A}} \tilde{\subseteq} \dot{\tilde{B}} = \{\dot{\tilde{p}}_1, \dot{\tilde{p}}_3\}$, then:

$$\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right) = \begin{Bmatrix} \dot{\tilde{F}}_{\dot{\tilde{p}}_1} = \left\{\left(\dot{\tilde{h}}_1, 0.3, 0.7\right), \left(\dot{\tilde{h}}_2, 0.5, 0.4\right), \left(\dot{\tilde{h}}_3, 0.6, 0.4\right), \left(\dot{\tilde{h}}_4, 0.7, 0.2\right)\right\} \\ \dot{\tilde{F}}_{\dot{\tilde{p}}_3} = \left\{\left(\dot{\tilde{h}}_1, 0.8, 0.2\right), \left(\dot{\tilde{h}}_2, 0.4, 0.6\right), \left(\dot{\tilde{h}}_3, 0.2, 0.5\right), \left(\dot{\tilde{h}}_4, 0.0, 0.9\right)\right\} \end{Bmatrix}, \text{ and}$$

$$[(\dot{\tilde{\mu}}_{43}, \dot{\tilde{v}}_{43})]_{m\times n} = \begin{bmatrix} (0.3, 0.7) & 0 & (0.8, 0.2) \\ (0.5, 0.4) & 0 & (0.4, 0.6) \\ (0.6, 0.4) & 0 & (0.2, 0.5) \\ (0.7, 0.2) & 0 & (0.0, 0.9) \end{bmatrix}.$$

Definition 2: If $\dot{\tilde{\mu}}_{ij} = 0$ and $\dot{\tilde{v}}_{ij} = 0$ $\forall i, j$, then $\dot{\tilde{A}}$ is known as zero IFSMs, where $\dot{\tilde{A}} = [(\dot{\tilde{\mu}}_{ij}, \dot{\tilde{v}}_{ij})]$ belongs to IFSM of order $m \times n$ [7].

Definition 3: If $\dot{\tilde{\mu}}_{ij}{}' \leq \dot{\tilde{\mu}}_{ij}{}''$ and $\dot{\tilde{v}}_{ij}{}' \geq \dot{\tilde{v}}_{ij}{}''$ $\forall i, j$, then $\dot{\tilde{A}}$ is known as a sub-matrice of IFSMs of $\dot{\tilde{B}}$, where $\dot{\tilde{A}} = [(\dot{\tilde{\mu}}_{ij}{}', \dot{\tilde{v}}_{ij}{}')]$ and $\dot{\tilde{B}} = [(\dot{\tilde{\mu}}_{ij}{}'', \dot{\tilde{v}}_{ij}{}'')]$. It is represented as $\dot{\tilde{A}} \tilde{\subseteq} \dot{\tilde{B}}$ [7].

Definition 4: Let $\dot{\tilde{A}} = \left[\left(\dot{\tilde{\mu}}^{\dot{\tilde{A}}}{}_{ij}, \dot{\tilde{v}}^{\dot{\tilde{A}}}{}_{ij}\right)\right] \in IFSM_{m\times n}$, then the complement of $\dot{\tilde{A}}$ denoted by $\dot{\tilde{A}}^o$ is defined as $\dot{\tilde{A}}^o = \left[\left(\dot{\tilde{\mu}}^{\dot{\tilde{A}}}{}_{ij}, \dot{\tilde{v}}^{\dot{\tilde{A}}}{}_{ij}\right)\right]$ $\forall i, j$ [7].

Definition 5: Let $\dot{\tilde{A}} = [(\dot{\tilde{\mu}}_{ij}{}', \dot{\tilde{v}}_{ij}{}')]$ and $\dot{\tilde{B}} = [(\dot{\tilde{\mu}}_{ik}{}'', \dot{\tilde{v}}_{ik}{}'')] \in IFSM_{m\times n}$, then '$\dot{\tilde{X}}$' product of $\dot{\tilde{A}}$ and $\dot{\tilde{B}}$ is defined by $\dot{\tilde{X}}: IFSM_{m\times n} \times IFSM_{m\times n} \longrightarrow IFSM_{m\times n^2}$, such that $\dot{\tilde{A}} \times \dot{\tilde{B}} = [(\dot{\tilde{\mu}}_{ij}{}', \dot{\tilde{v}}_{ij}{}')] \times [(\dot{\tilde{\mu}}_{ik}{}'', \dot{\tilde{v}}_{ik}{}'')] = [(\dot{\tilde{\mu}}_{ip}, \dot{\tilde{v}}_{ip})]$, where $\dot{\tilde{\mu}}_{ip} = max\{\dot{\tilde{\mu}}_{ij}{}', \dot{\tilde{\mu}}_{ik}{}''\}$ and $\dot{\tilde{v}}_{ip} = \min\{\dot{\tilde{v}}_{ij}{}', \dot{\tilde{v}}_{ik}{}''\}$ [3].

3. Application of Intuitionistic Fuzzy Soft Matrices in Medical Diagnosis

Suppose a set of symptoms $\dot{\tilde{Z}}$ of patients affected by diabetes $\dot{\tilde{D}}$, and $\dot{\tilde{P}}$ is the set of patients having symptoms in $\dot{\tilde{Z}}$, then $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ is IFS and can take matrix $\dot{\tilde{A}}$ from IFS $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$. Hence, $\dot{\tilde{A}}$ is the symptoms-disease matrix. If we take the complement of $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$, it becomes $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)^o$. Then, $\dot{\tilde{A}}^o$ is a matrix of non-symptom disease. Similarly, there is the IFS $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)$ over $\dot{\tilde{P}}$. Then, $\dot{\tilde{B}}$ is the patient's symptom and complement of $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)$ becomes $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)^o$. Then, $\dot{\tilde{B}}^o$ is known as the patient non-symptoms matrix. If we take, $\dot{\tilde{R}}_1 = \dot{\tilde{B}}\dot{\tilde{A}}$, then $\dot{\tilde{R}}_1$ is patient symptom disease matrix and $\dot{\tilde{R}}_2 = \dot{\tilde{B}}\dot{\tilde{A}}^o$ is patient symptoms non-disease matrix. Similarly, $\dot{\tilde{R}}_3 = \dot{\tilde{B}}^o \dot{\tilde{A}}$ is a patient non-symptoms disease matrix and $\dot{\tilde{R}}_4 = \dot{\tilde{B}}^o \dot{\tilde{A}}^o$ is the patient non-symptom non-disease matrix. The membership value of matrices can be written as MV$\left(\dot{\tilde{R}}_1\right)$, MV$\left(\dot{\tilde{R}}_2\right)$, MV$\left(\dot{\tilde{R}}_3\right)$, and MV$\left(\dot{\tilde{R}}_4\right)$. We can find out the diagnosis score $\dot{\tilde{X}}_{\dot{\tilde{R}}_1}$ for disease and $\dot{\tilde{X}}_{\dot{\tilde{R}}_2}$ against disease; i.e. $\dot{\tilde{X}}_{\dot{\tilde{R}}_1} = \left[\dot{\tilde{Y}}\left(\dot{\tilde{R}}_1\right)_{ij}\right]_{m*n}$, where $\dot{\tilde{Y}}\left(\dot{\tilde{R}}_1\right)_{ij} = \delta\left(\dot{\tilde{R}}_1\right)_{ij} - \delta\left(\dot{\tilde{R}}_3\right)_{ij}$, and $\dot{\tilde{X}}_{\dot{\tilde{R}}_2} = \left[\dot{\tilde{Y}}\left(\dot{\tilde{R}}_2\right)_{ij}\right]_{m*n}$, where $\dot{\tilde{Y}}\left(\dot{\tilde{R}}_2\right)_{ij} = \delta\left(\dot{\tilde{R}}_2\right)_{ij} - \delta\left(\dot{\tilde{R}}_4\right)_{ij}$.

3.1. Algorithm

Making the best choice for diabetes mellitus therapy involves weighing several clinical, individual, and environmental variables. Figure 1 represents the stepwise proposed algorithm.

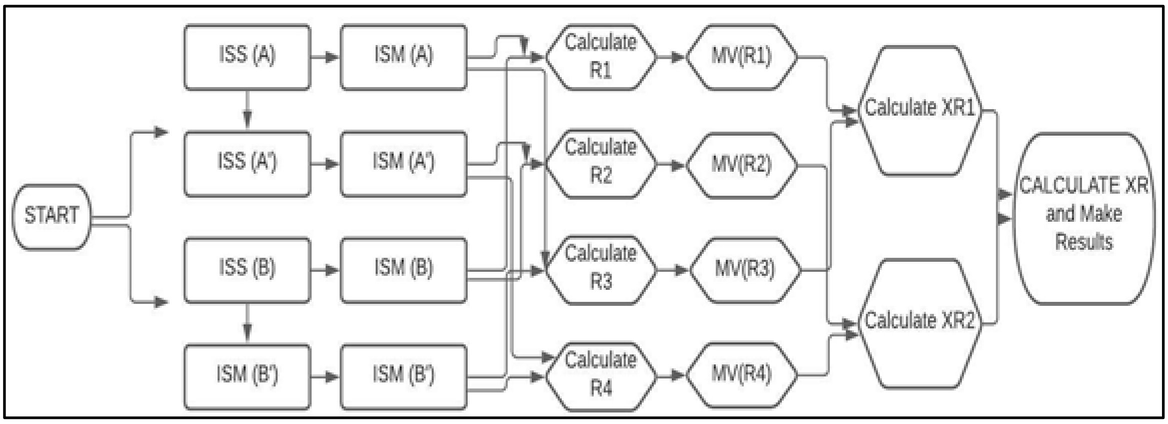

Fig. 1. Graphical representation of the proposed algorithm

With the use of IFSMs, this approach aims to improve the decision-making process's accuracy and depth. By using IFSMs, we want to capture both the inherent ambiguities and hesitancies that frequently accompany decisions about medical treatment in addition to the quantitative components. This algorithm offers an organized method for evaluating and choosing the best diabetes treatment plan, serving as a useful manual for both patients and healthcare providers. As a result, patient outcomes and care quality are improved.

We provide a thorough stepwise method that is organized and systematic to help with this important decision-making process:

Step 1 – Take the IFSS $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ and determine $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)^o$, as well as create corresponding matrices $\dot{\tilde{A}}$ and $\dot{\tilde{A}}^o$.

Step 2 – Take the IFSS $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)$ and determine $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)^o$, as well as create corresponding matrices $\dot{\tilde{B}}$ and $\dot{\tilde{B}}^o$.

Step 3 – Determine $\dot{\tilde{R}}_1 = \dot{\tilde{B}}\dot{\tilde{A}}, \dot{\tilde{R}}_2 = \dot{\tilde{B}}\dot{\tilde{A}}^o, \dot{\tilde{R}}_3 = \dot{\tilde{B}}^o\dot{\tilde{A}}$, and $\dot{\tilde{R}}_4 = \dot{\tilde{B}}^o\dot{\tilde{A}}^o$.

Step 4 – Determine MV$\left(\dot{\tilde{R}}_1\right)$, MV$\left(\dot{\tilde{R}}_2\right)$, MV$\left(\dot{\tilde{R}}_3\right)$, and MV$\left(\dot{\tilde{R}}_4\right)$.

Step 5 – Determine the diagnosis values $\dot{\tilde{X}}_{\dot{\tilde{R}}_1}$ and $\dot{\tilde{X}}_{\dot{\tilde{R}}_2}$.

Step 6 – Find $\dot{\tilde{X}}_k = \max\left[\dot{\tilde{X}}_{\dot{\tilde{R}}_1}\left(\dot{\tilde{p}}_i \dot{\tilde{d}}_j\right) - \dot{\tilde{X}}_{\dot{\tilde{R}}_2}\left(\dot{\tilde{p}}_i \dot{\tilde{d}}_j\right)\right]$. We judge, the patient $\dot{\tilde{p}}_i$ of disease $\dot{\tilde{d}}_k$.

Step 7 – $\dot{\tilde{X}}_k$ maybe two or more values. In this case, repeat the whole process by calculating symptoms for patients.

3.2. Case Study

In this case study, a 45-year-old man with recently diagnosed diabetes mellitus must decide between two main treatment options: lifestyle modification and oral medications (for the management of type-2 diabetes and insulin therapy for the management of type-1 diabetes or type-2 in severe instances. Using MCDM, important factors like blood sugar control, lifestyle impact, patient preferences, cost of treatment, and long-term health outcomes are weighed. The analysis shows that insulin therapy is the best option despite some lifestyle disruption and cost issues because of its superior blood sugar control and long-term health advantages. MCDM offers a methodical method for making personalized healthcare decisions as well as optimizing the choice of treatments for better health and quality of life results. Let three diabetic patients $\dot{\tilde{p}}_1, \dot{\tilde{p}}_2, \text{and } \dot{\tilde{p}}_3$ are hospitalized and take a universal set $\dot{\tilde{Z}} = \left\{\dot{\tilde{f}}_1, \dot{\tilde{f}}_2, \dot{\tilde{f}}_3\right\}$, where $\dot{\tilde{f}}_1, \dot{\tilde{f}}_2, \text{and } \dot{\tilde{f}}_3$ are appearing as symptoms of weight loss, polyuria, fatigue, polydipsia, and polyphagia, respectively. Consider a set of attributes is $\dot{\tilde{D}} = \left\{\dot{\tilde{d}}_1, \dot{\tilde{d}}_2\right\}$, where $\dot{\tilde{d}}_1 \text{ and } \dot{\tilde{d}}_2$ appearing for symptoms in diabetic patients of type-1 and type-2, respectively.

Step 1 – Suppose that $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ is an IFS over $\dot{\tilde{Z}}$, where $\dot{\tilde{F}}_{\dot{\tilde{A}}}$ is defined as $\dot{\tilde{F}}_{\dot{\tilde{A}}} : \dot{\tilde{D}} \to \dot{\tilde{F}}\left(\dot{\tilde{Z}}\right)$:

$$\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right) = \begin{Bmatrix} \dot{\tilde{F}}_{\dot{\tilde{A}}}\left(\dot{\tilde{d}}_1\right) = \left\{\left(\dot{\tilde{f}}_1, 0.8, 0.1\right), \left(\dot{\tilde{f}}_2, 0.5, 0.2\right), \left(\dot{\tilde{f}}_3, 0.6, 0.1\right)\right\} \\ \dot{\tilde{F}}_{\dot{\tilde{A}}}\left(\dot{\tilde{d}}_2\right) = \left\{\left(\dot{\tilde{f}}_1, 0.4, 0.7\right), \left(\dot{\tilde{f}}_2, 0.7, 0.2\right), \left(\dot{\tilde{f}}_3, 0.3, 0.8\right)\right\} \end{Bmatrix}$$

Now take the complement of $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ as:

$$\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)^o = \begin{Bmatrix} \dot{\tilde{F}}_{\dot{\tilde{A}}}\left(\dot{\tilde{d}}_1\right) = \left\{\left(\dot{\tilde{f}}_1, 0.2, 0.9\right), \left(\dot{\tilde{f}}_2, 0.5, 0.8\right), \left(\dot{\tilde{f}}_3, 0.4, 0.9\right)\right\} \\ \dot{\tilde{F}}_{\dot{\tilde{A}}}\left(\dot{\tilde{d}}_2\right) = \left\{\left(\dot{\tilde{f}}_1, 0.6, 0.3\right), \left(\dot{\tilde{f}}_2, 0.3, 0.8\right), \left(\dot{\tilde{f}}_3, 0.7, 0.2\right)\right\} \end{Bmatrix}$$, and write $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)$ and $\left(\dot{\tilde{F}}_{\dot{\tilde{A}}}, \dot{\tilde{D}}\right)^o$

in the form of matrices $\dot{\tilde{A}} = \begin{array}{c c} & \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{array}{c} \dot{\tilde{f}}_1 \\ \dot{\tilde{f}}_2 \\ \dot{\tilde{f}}_3 \end{array} & \begin{bmatrix} (0.8, 0.1) & (0.4, 0.7) \\ (0.5, 0.2) & (0.7, 0.2) \\ (0.6, 0.1) & (0.3, 0.8) \end{bmatrix} \end{array}$ and $\dot{\tilde{A}}^o = \begin{array}{c c} & \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{array}{c} \dot{\tilde{f}}_1 \\ \dot{\tilde{f}}_2 \\ \dot{\tilde{f}}_3 \end{array} & \begin{bmatrix} (0.2, 0.9) & (0.6, 0.3) \\ (0.5, 0.8) & (0.3, 0.8) \\ (0.4, 0.9) & (0.7, 0.2) \end{bmatrix} \end{array}$.

Step 2 – Now let a universal set $\dot{\tilde{P}} = \{\dot{\tilde{p}}_1, \dot{\tilde{p}}_2, \dot{\tilde{p}}_3\}$, where $\dot{\tilde{p}}_1, \dot{\tilde{p}}_2, \text{and } \dot{\tilde{p}}_3$ appear as hospitalized patients, and $\dot{\tilde{Z}} = \left\{\dot{\tilde{f}}_1, \dot{\tilde{f}}_2, \dot{\tilde{f}}_3\right\}$ as a set of attributes. Suppose that $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)$ is an IFS over $\dot{\tilde{Z}}$, where $\dot{\tilde{F}}_{\dot{\tilde{B}}}$ is defined as $\dot{\tilde{F}}_{\dot{\tilde{B}}} : \dot{\tilde{Z}} \to \dot{\tilde{F}}\left(\dot{\tilde{P}}\right)$:

$$\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right) = \begin{Bmatrix} \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_1\right) = \{(\dot{\tilde{p}}_1, 0.2, 0.6), (\dot{\tilde{p}}_2, 0.8, 0.4), (\dot{\tilde{p}}_3, 0.5, 0.9)\} \\ \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_2\right) = \{(\dot{\tilde{p}}_1, 0.9, 0.1), (\dot{\tilde{p}}_2, 0.4, 0.3), (\dot{\tilde{p}}_3, 0.7, 0.3)\} \\ \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_3\right) = \{(\dot{\tilde{p}}_1, 0.6, 0.3), (\dot{\tilde{p}}_2, 0.3, 0.2), (\dot{\tilde{p}}_3, 0.1, 0.5)\} \end{Bmatrix},$$

and its complement is:

$$\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)^o = \begin{Bmatrix} \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_1\right) = \{(\dot{\tilde{p}}_1, 0.8, 0.4), (\dot{\tilde{p}}_2, 0.2, 0.6), (\dot{\tilde{p}}_3, 0.5, 0.9)\} \\ \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_2\right) = \{(\dot{\tilde{p}}_1, 0.1, 0.9), (\dot{\tilde{p}}_2, 0.6, 0.7), (\dot{\tilde{p}}_3, 0.3, 0.7)\} \\ \dot{\tilde{F}}_{\dot{\tilde{B}}}\left(\dot{\tilde{f}}_3\right) = \{(\dot{\tilde{p}}_1, 0.4, 0.7), (\dot{\tilde{p}}_2, 0.7, 0.8), (\dot{\tilde{p}}_3, 0.9, 0.5)\} \end{Bmatrix}.$$

Write $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)$ and $\left(\dot{\tilde{F}}_{\dot{\tilde{B}}}, \dot{\tilde{Z}}\right)^o$ in the form of matrices $\dot{\tilde{B}}$ and $\dot{\tilde{B}}^o$; i.e.:

$$\dot{\tilde{B}} = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{ccc} \dot{\tilde{f}}_1 & \dot{\tilde{f}}_2 & \dot{\tilde{f}}_3 \end{array} \\ \begin{bmatrix} (0.2, 0.6) & (0.9, 0.1) & (0.6, 0.3) \\ (0.8, 0.4) & (0.4, 0.3) & (0.3, 0.2) \\ (0.5, 0.1) & (0.7, 0.3) & (0.1, 0.5) \end{bmatrix} \end{array} \text{ and } \dot{\tilde{B}}^o = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{ccc} \dot{\tilde{f}}_1 & \dot{\tilde{f}}_2 & \dot{\tilde{f}}_3 \end{array} \\ \begin{bmatrix} (0.8, 0.4) & (0.1, 0.9) & (0.4, 0.7) \\ (0.2, 0.6) & (0.6, 0.7) & (0.7, 0.8) \\ (0.5, 0.9) & (0.3, 0.7) & (0.9, 0.5) \end{bmatrix} \end{array}.$$

Steps 3 and 4 – Now there is:

$$\dot{\tilde{R}}_1 = \dot{\tilde{B}}.\dot{\tilde{A}} = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} (0.6, 0.2) & (0.4, 0.6) \\ (0.8, 0.2) & (0.4, 0.3) \\ (0.5, 0.1) & (0.7, 0.3) \end{bmatrix} \end{array}, \ \dot{\tilde{R}}_2 = \dot{\tilde{B}}.\dot{\tilde{A}}^o = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} (0.5, 0.8) & (0.6, 0.6) \\ (0.5, 0.8) & (0.6, 0.2) \\ (0.5, 0.8) & (0.5, 0.3) \end{bmatrix} \end{array},$$

$$\dot{\tilde{R}}_3 = \dot{\tilde{B}}^o.\dot{\tilde{A}} = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} (0.8, 0.4) & (0.4, 0.7) \\ (0.6, 0.6) & (0.6, 0.8) \\ (0.6, 0.5) & (0.4, 0.7) \end{bmatrix} \end{array}, \ \dot{\tilde{R}}_4 = \dot{\tilde{B}}^o.\dot{\tilde{A}}^o = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} (0.9, 0.4) & (0.6, 0.4) \\ (0.7, 0.8) & (0.7, 0.6) \\ (0.4, 0.8) & (0.7, 0.5) \end{bmatrix} \end{array}.$$

Now their membership values are:

$$MV\left(\dot{\tilde{R}}_1\right) = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} 0.4 & -0.2 \\ 0.6 & 0.1 \\ 0.4 & 0.4 \end{bmatrix} \end{array}, \ MV\left(\dot{\tilde{R}}_2\right) = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} -0.3 & 0.0 \\ -0.3 & 0.4 \\ -0.3 & 0.2 \end{bmatrix} \end{array},$$

$$MV\left(\dot{\tilde{R}}_3\right) = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} 0.4 & -0.3 \\ 0.0 & -0.2 \\ 0.1 & -0.3 \end{bmatrix} \end{array}, \ MV\left(\dot{\tilde{R}}_4\right) = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} 0.5 & 0.2 \\ -0.1 & 0.1 \\ -0.4 & 0.2 \end{bmatrix} \end{array}.$$

Step 5 – Diagnosis values (Figure 2) are $\dot{\tilde{X}}_{\dot{\tilde{R}}_1} = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} 0.0 & 0.1 \\ 0.6 & 0.3 \\ 0.3 & 0.7 \end{bmatrix} \end{array}$ and $\dot{\tilde{X}}_{\dot{\tilde{R}}_2} = \begin{array}{c} \\ \dot{\tilde{p}}_1 \\ \dot{\tilde{p}}_2 \\ \dot{\tilde{p}}_3 \end{array} \begin{array}{c} \begin{array}{cc} \dot{\tilde{d}}_1 & \dot{\tilde{d}}_2 \end{array} \\ \begin{bmatrix} -0.8 & -0.2 \\ -0.2 & 0.3 \\ 0.1 & 0.0 \end{bmatrix} \end{array}$.

Step 6 – In the last step, we calculate $\dot{\tilde{X}}_{\dot{\tilde{R}}_1}\left(\dot{\tilde{p}}_i\dot{\tilde{d}}_j\right) - \dot{\tilde{X}}_{\dot{\tilde{R}}_2}\left(\dot{\tilde{p}}_i\dot{\tilde{d}}_j\right)$ to finalize the type of diabetes (Table 1). By max value, the conclusion is that $\dot{\tilde{p}}_1$ and $\dot{\tilde{p}}_2$ are diabetic patients of type-1 whereas $\dot{\tilde{p}}_3$ is type-2.

Table 1
Detailed results

$\dot{\tilde{X}}_{\dot{\tilde{R}}_1} - \dot{\tilde{X}}_{\dot{\tilde{R}}_2}$	$\dot{\tilde{d}}_1$	$\dot{\tilde{d}}_2$	Max. value
$\dot{\tilde{p}}_1$	0.8	0.3	0.8
$\dot{\tilde{p}}_2$	0.8	0.0	0.8
$\dot{\tilde{p}}_3$	0.2	0.7	0.7
$\dot{\tilde{p}}_1$	0.8	0.3	0.8

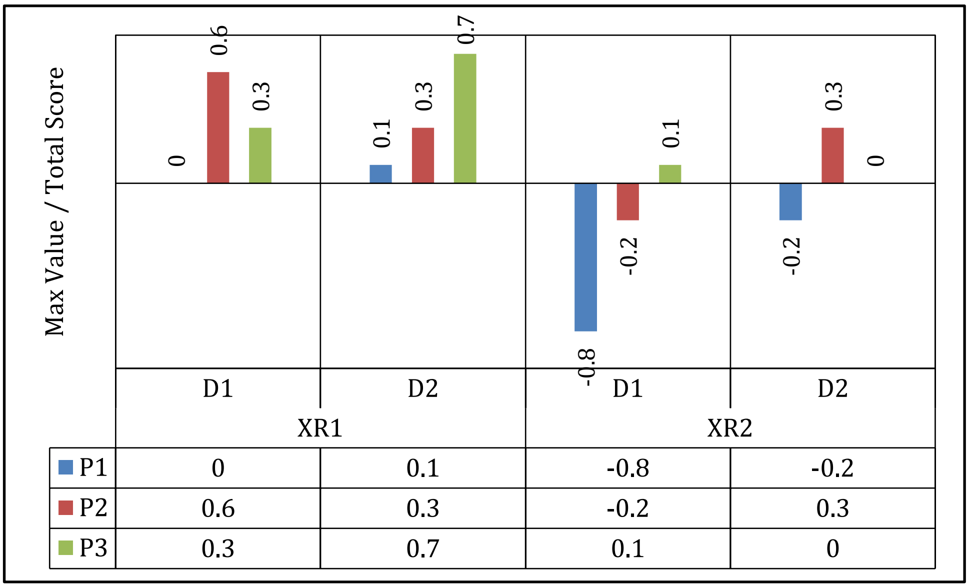

Fig. 2. Graphical representation of the case study

4. Conclusions

IFSMs were used to solve the diabetic treatment selection case study. This method is a unique and promising one for making healthcare decisions. By considering not only the conventional quantitative criteria but also the doubts and hesitancies connected to patient preferences and subjective judgments, the application of IFSM enables a more thorough and nuanced assessment of the treatment alternatives. This method is a great tool for boosting the decision-making process since it is in line with the inherently unpredictable character of medical decision-making.

Fuzzy logic or MCDM studies offer insightful information, but they might not fully capture the intuitionistic and hesitation elements present in actual clinical situations. According to other studies in the field, the IFSM method presented in this study fills this gap by providing a stronger and more adaptable framework for decision-making in daily life issues. First off, the addition of IFSMs to clinical decision support systems is a big step in the right direction since it enables medical personnel to use this approach in practical settings. By making more individualized and nuanced treatment suggestions that are based on the needs of each patient, this application can improve the standard of care. Future studies might also investigate using machine learning for dynamic therapy changes and incorporating patient-specific characteristics like genetics and lifestyle.

This study's future directions provide intriguing opportunities for enhancing healthcare decision-making, particularly in the management of diabetes. Real-time monitoring and longitudinal data analysis are additional possible ways to make sure that treatment plans adapt to changing patient situations. The decision-making process may be further improved by doing thorough cost-benefit assessments and expanding the criteria to include patient-centered outcomes. The benefits of this study ultimately stem from its ability to improve decision quality, lessen problems, support personalized treatment, and contribute to the larger area of healthcare decision support, providing insightful information for better patient care and health outcomes.

Funding
This study did not receive any external financial support.

Conflicts of Interest

The author declares no conflicts of interest.

References

[1] Zadeh, L. A. (1965). Fuzzy Sets. *Information and Control, 8*, 338-353.

[2] Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning I. *Information Science, 8*, 199–249. https://doi.org/10.1016/0020-0255(75)90036-5.

[3] Pawlak, Z. (1982). Rough Sets. *International Journal of Computer and Information Science, 11*, 341-356.

[4] Antanassov, K. (1986). Intuitionistic fuzzy set. *Fuzzy Sets and Systems, 20*(1), 87-96.

[5] Gerstenkorn, T., & Mańko, J. (1991). Correlation of intuitionistic fuzzy sets. *Fuzzy Sets and Systems, 44*(1), 39-43. https://doi.org/10.1016/0165-0114(91)90031-K.

[6] Molodtsov, D. (1999). Soft Set Theory-First Results. *Computers and Mathematics with Applications, 37*, 19-31. https://doi.org/10.1016/S0898-1221(99)00056-5.

[7] Maji, P. K., Biswas R., & Roy, A. R. (2001). Fuzzy Soft Sets. *The Journal of Fuzzy Mathematics, 9*, 3, 589-602.

[8] Agarwal, M., Biswas, K. K., & Hanmandlu, M. (2013). Generalized intuitionistic fuzzy soft sets with applications in decision-making. *Applied Soft Computing, 13*(8), 3552-3566. https://doi.org/10.1016/j.asoc.2013.03.015.

[9] Jiang, Y., Tang, Y., Chen, Q., Liu, H., & Tang, J. (2010). Interval-valued intuitionistic fuzzy soft sets and their properties. *Computers & Mathematics with Applications, 60*(3), 906-918. https://doi.org/10.1016/j.camwa.2010.05.036.

[10] Garg, H., & Arora, R. (2018). Generalized and group-based generalized intuitionistic fuzzy soft sets with applications in decision-making. *Applied Intelligence, 48*, 343-356. https://doi.org/10.1007/s10489-017-0981-5.

[11] Maji, P. K. (2009). More on intuitionistic fuzzy soft sets. In *Rough Sets, Fuzzy Sets, Data Mining and Granular Computing*, Delhi, India, December 15-18, 2009. Proceedings 12 (pp. 231-240). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-10646-0_28.

[12] Khan, M. J., Kumam, P., Liu, P., Kumam, W., & Ashraf, S. (2019). A novel approach to generalized intuitionistic fuzzy soft sets and its application in decision support system. *Mathematics, 7*(8), 742. https://doi.org/10.3390/math7080742.

[13] Maji, P. K., Biswas R., & Roy, A. R. (2003). An application of soft sets in a decision-making problem. *Computer and Mathematics with Applications, 44*, 1077-1083.

[14] Chetia. B., Das. K. P. (2012). Some Results of Intuitionistic Fuzzy Soft Matrix theory. *Advances in Applied Science Research, 3*(1), 412-423.

[15] Muthukumar, P., & Krishnan, G. S. S. (2016). A similarity measure of intuitionistic fuzzy soft sets and its application in medical diagnosis. *Applied Soft Computing, 41*, 148-156. https://doi.org/10.1016/j.asoc.2015.12.002.

[16] Çağman, N., & Karataş, S. (2013). Intuitionistic fuzzy soft set theory and its decision making. *Journal of Intelligent & Fuzzy Systems, 24*(4), 829-836. https://doi.org/10.3233/IFS-2012-0601.

[17] Kharal, A., & Ahmad, B. (2009). Mappings on fuzzy soft classes. *Advances in Fuzzy System, 6*, 407890. https://doi.org/10.1155/2009/407890.

[18] Jafar, N. M., Muniba, K., Saeed, A., Abbas, S., & Bibi, I. (2019). Application of Sanchez's Approach to Disease Identification Using Trapezoidal Fuzzy Numbers. *International Journal of Latest Engineering Research and Applications, 4*(9), 51-57.

[19] Meo, A. S., Zia, I., Bukhari, A. I., & Arain, A. S. (2016). Type-2 diabetes mellitus in Pakistan: Current prevalence and future forecast. *Journal of the Pakistan Medical Association, 66*(12), 1637-1642.

[20] Jafar, M. N., Saqlain, M., Shafiq, A. R., Khalid, M., Akbar, H., & Naveed, A. (2020). New Technology in Agriculture Using Neutrosophic Soft Matrices with the Help of Score Function. *International Journal of Neutrosophic Science, 3*(2), 78-88.

[21] Jafar, M.N., Muniba, K., Saeed, A., Abbas, S., & Bibi, I. (2019). Application of Sanchez's Approach to Disease Identification Using Trapezoidal Fuzzy Numbers. *International Journal of Latest Engineering Research and Applications, 4*(9), 51-57.

[22] Tao, Z., Chen, H., Song, X., Zhou, L., & Liu, J. (2015). Uncertain linguistic fuzzy soft sets and their applications in group decision-making. *Applied Soft Computing, 34*, 587-605. https://doi.org/10.1016/j.asoc.2015.04.051.

[23] Vijayabalaji, S., & Ramesh, A. (2018). Uncertain multiplicative linguistic soft sets and their application to group decision-making. *Journal of Intelligent & Fuzzy Systems, 35*(3), 3883–3893. https://doi.org/10.3233/JIFS-18818.

[24] Wang, H., Ju, Y., & Liu, P. (2019). Multi-attribute group decision-making methods based on q-rung orthopair fuzzy linguistic sets. International Journal of Intelligent Systems, 34, 1129- 1157. https://doi.org/10.1002/int.22089.

[25] Wu, X., Liao, H., Benjamin, L., & Zavadskas, E. K. (2023). A Multiple Criteria Decision-Making Method with Heterogeneous Linguistic Expressions. *IEEE Transactions on Engineering Management, 70*(5), 1857-1870. https://doi.org/10.1109/TEM.2021.3072590.

[26] Saqlain M., Moin, S., Jafar, M. N., Saeed, M., & Smarandache, F. (2020). Aggregate Operators of Neutrosophic Hypersoft Set. *Neutrosophic Sets and Systems, 32*, 294-306. https://doi.org/10.5281/zenodo.3723155.

[27] Saqlain, M., Sana, M., Jafar, N., Saeed, M., & Said, B. (2020). Single and Multi-valued Neutrosophic Hypersoft set and Tangent Similarity Measure of Single valued Neutrosophic Hypersoft Sets. *Neutrosophic Sets and Systems, 32*, 317-329. https://doi.org/10.5281/zenodo.3723165.

[28] Saqlain, M., Saeed, M., Zulqarnain, M. R., & Sana, M. (2021). Neutrosophic Hypersoft Matrix Theory: Its Definition, Operators, and Application in Decision-Making of Personnel Selection Problem. *Neutrosophic Operational Research*, Springer. https://doi.org/10.1007/978-3-03057197-9.

[29] Saqlain M., Riaz, M., Saleem, M. A., & Yang, M. S. (2021). Distance and Similarity Measures for Neutrosophic HyperSoft Set (NHSS) with Construction of NHSSTOPSIS and Applications. *IEEE Access, 9*, 30803-30816. https://doi.org/10.1109/ACCESS. 2021.3059712.

[30] Jafar, M. N., Saeed, M., Saqlain, M., & Yang, M. S. (2021). Trigonometric similarity measures for neutrosophic hypersoft sets with application to renewable energy source selection. *Ieee Access, 9*, 129178-129187. https://doi.org/10.1109/ACCESS.2021.3112721.

[31] Jana, C., & Pal, M. (2023). Interval-Valued Picture Fuzzy Uncertain Linguistic Dombi Operators and Their Application in Industrial Fund Selection. *Journal of Industrial Intelligence, 1*(2), 110-124. https://doi.org/10.56578/jii010204.

[32] Saqlain, M. (2023). Sustainable Hydrogen Production: A Decision-Making Approach Using VIKOR and Intuitionistic Hypersoft Sets. *Journal of Intelligent Management Decision, 2*(3), 130-138. https://doi.org/10.56578/jimd020303.

[33] Jain, A., Kumar, V., & Kumar, R. (2017). A novel approach for medical decision support system using intuitionistic fuzzy soft matrix. *Health Information Science and Systems, 5*(1), 1-10.

[34] Majumdar, P., & Samanta, S. K. (2010). Generalized fuzzy soft sets. *Computers & Mathematics with Applications, 59*(4), 1425–1432. https://doi.org/10.1016/j.camwa.2009.12.006.

[35] Ali, M. I., Feng, F., Liu, X., Min, W. K., & Shabir, M. (2009). On some new operations in soft set theory. *Computers & Mathematics with Applications, 57*(9), 1547-1553. https://doi.org/10.1016/j.camwa.2008.11.009.

[36] Vijayabalaji, S., & Ramesh, A. (2018). Uncertain multiplicative linguistic soft sets and their application to group decision-making. *Journal of Intelligent & Fuzzy Systems, 35*(3), 3883-3893. https://doi.org/10.3233/JIFS-18818.

[37] Aiwu Z., & Hongjun G. (2016). Fuzzy-valued linguistic soft set theory and multi-attribute decision-making application. *Chaos, Solitons & Fractals, 89*, 2-7. https://doi.org/10.1016/j.chaos.2015.09.001.

[38] Tao, Z., Chen, H., Song, X., Zhou, L., & Liu, J. (2015). Uncertain linguistic fuzzy soft sets and their applications in group decision making. *Applied Soft Computing, 34*, 587-605. https://doi.org/10.1016/j.asoc.2015.04.051.