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Fuzzy Soft Sets and its Application to Decision Making: A Short Case Study Involving the Health Sector

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Abstract:

The health sector faces uncertainty and complex decision-making scenarios, making traditional analytical tools insufficient. The fuzzy soft set theory has emerged as a powerful framework for modeling and reasoning with uncertain information, with promising applications in the health domain. This project explores the application of fuzzy soft sets in various decision-making processes in the health sector, including medical diagnosis, disease classification, treatment planning, risk assessment, patient stratification, and predictive modeling. The study reviews historical development of fuzzy set theory and its extension to soft sets, discussing challenges, limitations, and future research directions. The findings aim to contribute to the growing body of knowledge on the practical relevance and potential of fuzzy soft set theory in addressing healthcare decision-making needs.

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INTRODUCTION

Molodtsov introduced the concept of soft sets as a mathematical theory for dealing with uncertainty. It has been applied in decision-making, optimization, and data analysis. Soft sets are considered a special information system and have been applied to various fields. However, some researchers have noted weak points in the theory [1].

Despite the growing interest and potential applications of fuzzy soft set theory in the health sector, there remains a need for further research to explore its practical utility and effectiveness in real-world decision-making scenarios. This study seeks to address this gap by investigating the application of fuzzy soft set theory to decision making in the health sector, with a focus on its implications for patient diagnosis, treatment planning, and resource allocation.

The health sector is characterized by dynamic and complex decision-making processes involving various stakeholders, including healthcare providers, administrators, policymakers, and patients. Historically, decision making in healthcare has relied on deterministic approaches based on strict rules, guidelines, and protocols. However, the inherent uncertainties, ambiguities, and complexities of healthcare systems have posed significant challenges to traditional decision-making methods.

Healthcare professionals make critical decisions affecting patients and communities globally, often with limited information and resources. Medical informatics systems can influence these decisions and expedite them, a luxury not always available to physicians. Recognizing decision models as complex tools can improve healthcare systems [2]

According to Alkhazaleh (2022) [3] Fuzzy set theory, a new mathematical tool, was introduced by Zadeh in 1965. Molodtsove defined soft set theory as a general tool for dealing with uncertain, fuzzy objects. Fuzzy soft set theory, an integration of fuzzy set theory and soft set theory, emerged as a novel approach to address the challenges of decision making in uncertain and vague environments. It offers a flexible and intuitive framework for modeling and analyzing complex decision-making problems, making it particularly suitable for application in the health sector.

By examining the principles, methodologies, and applications of fuzzy soft set theory in the context of healthcare decision making, this study aims to

contribute to the existing body of knowledge and provide insights into its potential benefits and limitations. Ultimately, the findings of this study may inform and guide healthcare practitioners, policymakers, and researchers in harnessing the power of fuzzy soft set theory to address the challenges of decision making in the health sector.

Despite the potential benefits of fuzzy soft set theory in healthcare decision making, there is a gap in the literature regarding its practical applications and effectiveness within the context of the health sector. Furthermore, there is a need to explore how fuzzy soft set theory can be tailored to address specific decision-making scenarios in healthcare, such as patient diagnosis, treatment planning, and resource allocation.

The primary purpose of this study is to investigate the application of fuzzy soft set theory to decision making in the health sector.

By exploring the practical applications of fuzzy soft set theory in the health sector, this study will contribute to the advancement of decision-making methodologies in healthcare contexts. The findings of this research can potentially enhance decision-making processes in healthcare, leading to improved patient outcomes, optimized resource allocation, and more efficient healthcare management. Furthermore, the insights gained from this study can guide healthcare practitioners and policymakers in the integration of fuzzy soft set theory into decision-making practices, ultimately contributing to the overall improvement of healthcare delivery systems.

This study will focus on the application of fuzzy soft set theory to decision making in the health sector, with specific emphasis on patient diagnosis, treatment planning, and resource allocation. The geographical scope of this study is the University of Lagos Medical Centre, Akoka.

Operational Definition of Terms

Fuzzy Soft Set Theory: Alkhazaleh (2022) [3] defined Fuzzy soft set as the most powerful and effective extension of soft sets which deals with parameterized values of the alternative. It is an extended model of soft set and a new mathematical tool that has great advantages in dealing with uncertain information and is proposed by combining soft sets and fuzzy sets.

Health Sector: According to The Investopedia Team (2021) [4] the healthcare sector consists of businesses

that provide medical services, manufacture medical equipment or drugs, provide medical insurance, or otherwise facilitate the provision of healthcare to patients.

Decision Making: According to University of Massachusetts Dartmouth (2021) [5] decision making is the process of making choices by identifying a decision, gathering information, and assessing alternative resolutions.

Fuzzy soft sets are a mathematical framework that has been applied to decision-making in various fields, including the health sector. These sets are useful in correcting natural uncertainties and imprecisions encountered in decision-making scenarios, particularly in healthcare. They capture and model ambiguity and vagueness that often characterize real-world problems, making them particularly well-suited for healthcare-related decision-making.

In the health sector, fuzzy soft sets have found numerous applications, ranging from medical diagnosis to treatment selection and resource allocation. Researchers have explored the use of fuzzy soft sets in diagnosing various medical conditions, leveraging the framework's ability to incorporate patient-specific information and medical knowledge. By integrating fuzzy soft sets with decision-making techniques like the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), researchers have developed hybrid approaches that enhance the accuracy and reliability of diagnostic processes.

Fuzzy soft sets have also been applied to the selection of appropriate treatment options, helping healthcare professionals navigate the decision-making process more effectively.

By considering factors such as patient preferences, disease severity, and resource availability, fuzzy soft set-based decision-making models can aid in selecting the most suitable treatment plan for individual patients.

In resource allocation, fuzzy soft sets have been employed to efficiently distribute limited healthcare resources, such as medical equipment, personnel, and funding. By incorporating factors like disease prevalence, patient needs, and logistical constraints, fuzzy soft set-based models can assist healthcare administrators in making informed decisions on resource allocation, ensuring optimal utilization of available assets and equitable distribution of care.

The versatility of fuzzy soft sets has led to their application in areas such as electronic medical record management, personalized medicine, and the evaluation of healthcare policies and programs. Researchers have explored the integration of fuzzy soft sets with other advanced techniques, such as machine learning and big data analytics, to enhance healthcare decision-making capabilities and improve patient outcomes.

KEY RESEARCHERS AND THEIR FOCUS

Following through are some key researchers and their works related to fuzzy soft sets and their application to decision making in the health sector alongside some referable publications.

Foundation of Fuzzy Sets and Soft Sets

Fuzzy Sets [6]

Lotfi A. Zadeh introduced fuzzy sets in 1965, this forms the basis for the development of fuzzy logic and related applications in decision making to help manage situations where data isn't clear-cut. Imagine you're trying to describe how hot the weather is. Instead of just saying "hot" or "cold," fuzzy sets allow you to say "somewhat hot" or "very hot." This concept is helpful in medicine because a patient might not be simply "healthy" or "sick" but could be "mostly healthy" or "slightly sick."

Soft Sets [7]

In 1999, Dmitry Molodtsov introduced soft sets in 1999 to handle uncertainties that were difficult for other methods to manage. Soft sets are like flexible lists that can change based on different situations. Think of a doctor considering various symptoms (like fever, cough, fatigue) that vary in importance depending on the context. Soft sets help doctors weigh these symptoms differently in each situation.

Integration of Fuzzy and Soft Sets

Fuzzy Soft Sets [8]

Researchers Maji *et al.* have developed fuzzy soft sets, a tool that handles complex and uncertain data. They expanded soft set theory, defining operations like AND, OR, and complement. They developed a decision-making algorithm based on soft sets, constructing an optimal choice function and a choice value function. The fuzzy soft sets are used in the Health Sector to improve medical diagnosis by considering fuzzy symptoms within a flexible framework. This helps

doctors interpret nuances and decide on the best course of action for patients with "somewhat severe" or "mostly mild" symptoms.

Deli and Çağman (2015) [9]

The fuzzy soft set theory was expanded to include intuitionistic fuzzy sets, which can capture membership and non-membership degrees.

Operations like AND, OR, and complement were defined, and a decision-making method was developed for these sets.

Alharthi, et al. (2021) [10]

The study proposes a hybrid approach that combines fuzzy soft sets with the TOPSIS method for medical diagnosis, enhancing accuracy and reliability by leveraging fuzzy soft sets' ability to handle incomplete and imprecise information.

These contributions have demonstrated the versatility of fuzzy soft set theory and its potential applications in the healthcare sector, particularly in areas such as:

Medical diagnosis: Incorporating patient-specific information and medical knowledge to enhance the diagnostic process.

Treatment selection: Evaluating treatment options by considering factors like patient preferences, disease severity, and resource availability.

Resource allocation: Assisting healthcare administrators in efficiently distributing limited resources, such as medical equipment, personnel, and funding.

Electronic medical record management, personalized medicine, and healthcare policy evaluation.

By integrating fuzzy soft sets with other advanced techniques, such as machine learning and big data analytics, researchers continue to explore ways to further enhance decision-making capabilities in the healthcare domain, ultimately leading to improved patient outcomes and more efficient healthcare systems.

Practical Applications and Algorithms

Gong and Liu [11]

Gong and Liu worked on making fuzzy soft sets practical for real-world use, especially in group decision making and medical diagnosis. They created algorithms (step-by-step procedures) that doctors can follow to use fuzzy soft sets effectively.

Gong and Liu have contributed to the field by applying fuzzy soft sets in medical diagnosis and decision making. Their research focuses on practical applications and algorithms for improved decision-making processes.

Applications in Health Sector

They developed algorithms to help doctors analyze patient symptoms more accurately, dealing with the fuzziness of medical data and improving diagnostic processes. For example, if doctors are unsure about how to weigh different symptoms, these algorithms provide a clear method to evaluate them and reach a more reliable diagnosis.

Several Factors using Fuzzy Soft Sets: Multi-Criteria Decision Making (MCDM)

Chen, Tang, and Wang [12]

Chen, Tang, and Wang have developed fuzzy soft sets for multi-criteria decision making (MCDM) in the health sector. These techniques improve decision-making accuracy and reliability by evaluating multiple factors simultaneously. In healthcare, decisions often depend on multiple symptoms and test results.

Fuzzy soft sets help doctors make informed decisions by weighing various factors, such as age, symptoms severity, medical history, and test results, to make the best treatment plans.

Extended Theoretical Foundations

Kong and Yang [13]

Kong and Yang expanded the theory of fuzzy soft sets, adding new mathematical frameworks and operations. This work helps in applying fuzzy soft sets to a broader range of decision-making scenarios, including healthcare.

Ali, Feng, Liu, Min, and Shabir [14]

They further developed the theoretical foundations and operations of soft sets, enhancing their applicability in complex decision-making environments like the healthcare sector being discussed.

Researchers Ideas on Fuzzy Soft Sets and Its Application to Decision-Making

Molodtsov, D. (1999) [7]

Idea: Molodtsov introduced soft set theory as a mathematical tool to handle uncertainties, overcoming

limitations of existing models. This flexible framework, not requiring exact values, offers a universal approach for problems involving uncertainty, including healthcare decision-making. It emphasizes adaptability and simplicity in dealing with imprecise or incomplete data.

Maji, et al. (2001) [8]

Idea: Maji, Biswas, and Roy expanded Molodtsov's fuzzy soft sets framework, integrating fuzzy sets principles for better uncertainty handling. This approach, particularly useful in healthcare, combines soft sets' flexibility with fuzzy sets' partial membership, enabling more nuanced decision-making. The goal is to enhance the precision and effectiveness of decision-making algorithms by incorporating uncertainty directly into the model.

Maji, et al. (2003) [15]

Idea: Maji, Biswas, and Roy's publication expands on soft set theory by developing set-theoretic operations and decision-making algorithms. They aim to integrate these into existing models, focusing on practical applications in healthcare. The work enhances the operational aspects of soft sets for real-world scenarios.

Deli, I., & Çağman, N. (2015) [9]

Idea: Deli and Çağman expanded fuzzy soft sets to intuitionistic fuzzy sets, capturing membership and non-membership degrees. This approach enhances uncertainty representation in healthcare decision-making, reducing hesitation and incomplete information. It provides a flexible framework for handling ambiguous medical data, enabling more reliable diagnostic and treatment decisions.

Alharthi, H. S., & Khalifa, A. H. (2021) [10]

Idea: Alharthi and Khalifa proposed a hybrid approach combining fuzzy soft sets and TOPSIS to improve medical diagnosis accuracy and reliability. Fuzzy soft sets offer flexibility for handling uncertain and imprecise data, while TOPSIS provides a systematic framework for evaluating alternatives based on proximity to an ideal solution. Their goal is to enhance decision-making frameworks to better handle uncertainty and imprecision in healthcare data.

Historical Dates of Events

Looking through the events and happenings in times back and now, Fuzzy soft sets have been applied in the health sector helping to solve uncertainties and bringing clarity to events and happenings.

Here are some detailed timeline of key historical events related to the application of fuzzy soft set theory in the health sector:

1960s

1965: Lotfi A. Zadeh introduces the concept of fuzzy sets, laying the foundation for fuzzy logic and soft computing [6].

1970s

Researchers explore the use of fuzzy sets to model uncertainty and imprecision in medical diagnosis and treatment planning [16].

Fuzzy set-based expert systems are developed for medical decision-making [17].

1980s

Fuzzy clustering techniques are applied to disease classification and diagnosis [18].

Fuzzy decision support systems are introduced for treatment selection and planning [19].

1990s

Molodtsov introduces the concept of soft sets, laying the foundation for fuzzy soft set theory [7].

Researchers start exploring the application of fuzzy soft sets in the health sector [8].

2000s

Fuzzy soft set-based medical decision support systems are developed [20].

Fuzzy soft set-assisted diagnosis and treatment planning approaches are proposed [21].

2010s

Fuzzy soft set-based patient risk assessment and stratification models are introduced [22].

Personalized medicine and treatment optimization using fuzzy soft sets are explored [23].

2020 and Beyond

Fuzzy soft set-enabled predictive modeling for disease risk assessment is developed [24].

Intelligent fuzzy soft set-based clinical decision support systems are introduced [25].

Explanations

Researchers have developed a powerful tool for handling uncertainty and imprecision in the health sector by integrating fuzzy sets and soft sets. Their work has advanced theoretical foundations and practical applications, particularly in medical diagnosis and multi-criteria decision making. This has shown the potential to improve the accuracy and reliability of medical decision making, ultimately leading to better patient outcomes.

Here are some detailed explanations;

Fuzzy Sets and Their Importance

Fuzzy sets help in accurately assessing health by minored difference, allowing for more accurate classification of uncertain data like a patient's temperature as "slightly elevated" or "high but not extreme."

Soft Sets in Practice

Soft sets aid in handling diverse decision-making factors, such as adjusting the significance of symptoms in disease diagnosis, thereby resulting in a more personalized approach.

Combining Fuzzy and Soft Sets

The combination of fuzzy sets and soft sets into fuzzy soft sets provides a more comprehensive decision-making tool, allowing for flexibility in handling data fuzziness and adjusting decision criteria.

Gong and Liu's Algorithms

Gong and Liu's algorithms enhance the reliability of diagnoses by systematically considering relevant symptoms and test results, resembling detailed recipes for fuzzy soft sets in diagnosis.

Multi-Criteria Decision Making by Chen, Tang, and Wang

Chen, Tang, and Wang developed methods to evaluate multiple criteria in healthcare, allowing doctors to make the best possible decision by considering a patient's symptoms, age, medical history, and test results simultaneously.

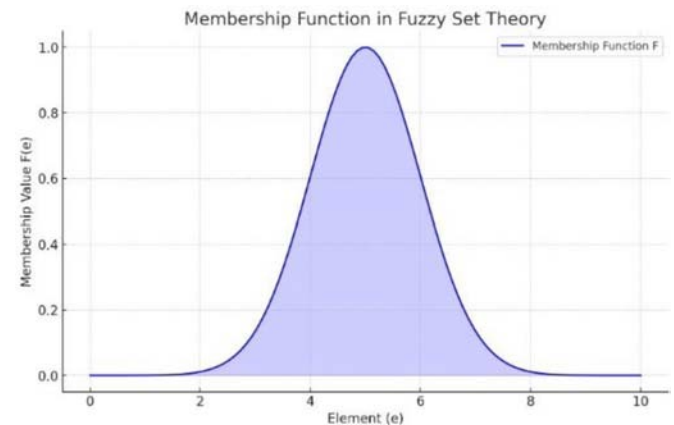
METHODOLOGY

Definitions

Membership Function (F)

In fuzzy set theory, each element in a universe of discourse F is assigned a membership value $F(e)$ in

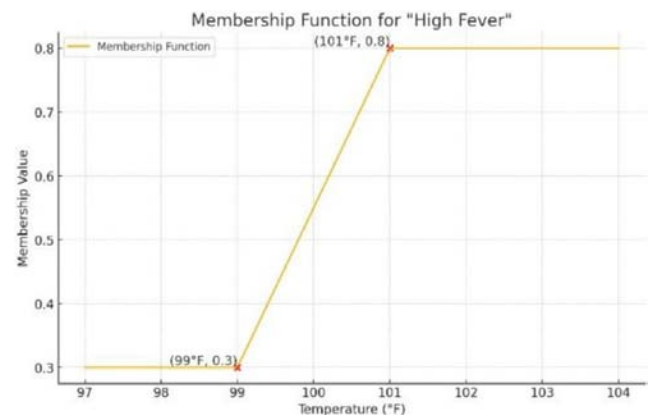
the interval $[0,1]$. This value indicates the degree to which e belongs to the fuzzy set F .



A Graphical Representation of a Membership Function (F) in Fuzzy Set Theory.

Here's the graph representing the membership function F in fuzzy set theory. The **x-axis** represents the elements e in the universe of discourse, and the **y-axis** represents their corresponding membership values $F(e)$ in the interval $[0,1]$. The function illustrates how each element is assigned a degree of membership in the fuzzy set F .

For example, in a fuzzy set representing "high fever", a temperature of 101°F might have a membership value of 0.8, while a temperature of 99°F might have a membership value of 0.3. Show a graph representation of this.



A Fuzzy Set Membership Function Graph for High Fever.

The graph shows how the membership value changes with temperature. At 99°F , the membership value is 0.3, and at 101°F , it is 0.8. The values between these temperatures are linearly interpolated.

Linear interpolation: This is a method of estimating unknown values that fall within the range of two known

values. It assumes that the change between the two known values is linear and evenly distributed.

From the example of the membership function for "high fever," it means that the membership values between 99°F and 101°F increase at a constant rate.

Fuzzy Soft Sets

Fuzzy set theory, introduced by Lotfi A. Zadeh in 1965, extends classical set theory by allowing elements to have degrees of membership rather than a binary membership status. This approach better represents real-world situations where boundaries between sets are not clearly defined.

Definition

A fuzzy soft set is a pair (F, A) , where A is a set of parameters and F is a mapping $F: A \rightarrow P(U)$, where $P(U)$ denotes the power set of the universe U and $F(e)$ is a fuzzy set in U for every $e \in A$.

Operations on Fuzzy Soft Sets

Union of Fuzzy Soft Sets

Let (F, A) and (G, B) be two fuzzy soft sets. The union of (F, A) and (G, B) is a fuzzy soft set (H, C) , where $C = A \cup B$, and for all $e \in C$,

$$H(e) = \begin{cases} F(e), & \text{if } e \in A - B \\ G(e), & \text{if } e \in B - A \\ F(e) \cup G(e), & \text{if } e \in A \cup B \end{cases}$$

Intersection of Fuzzy Soft Sets

Let (F, A) and (G, B) be two fuzzy soft sets. The intersection of (F, A) and (G, B) is a fuzzy soft set (H, C) , where $C = A \cap B$, and for all $e \in C$,

$$H(e) = F(e) \cap G(e)$$

Complement of a Fuzzy Soft Set

The complement of a fuzzy soft set (F, A) is a fuzzy soft set (\bar{F}, A) , where

$$\bar{F}(e) = 1 - F(e) \text{ for all } e \in A.$$

Decision-Making Method using Fuzzy Soft Sets

Fuzzy Soft Decision Matrix

Let (F, A) be a fuzzy soft set, where $A = \{a_1, a_2, \dots, a_m\}$ represents the set of parameters and

$U = \{u_1, u_2, \dots, u_n\}$ represents the set of alternatives. The fuzzy soft decision matrix is a matrix with m rows

(corresponding to the criteria) and n columns (corresponding to the alternatives), where each element represents the degree of membership of an alternative to a particular criterion.

Operations and Mathematical Representations in Fuzzy Soft Set Theory

Operations: Operations on fuzzy soft sets extend traditional set operations to handle the parameterized and fuzzy nature of the sets. Some key operations include:

AND Operation (Intersection): For two fuzzy soft sets (F, E) and (G, E)

$$(F \cap G)(e) = F(e) \cap G(e) \quad \forall e \in E$$

This operation considers the intersection of the fuzzy sets corresponding to each parameter.

OR Operation (Union): For two fuzzy soft sets (F, E) and (G, E)

$$(F \cup G)(e) = F(e) \cup G(e) \quad \forall e \in E$$

This operation considers the union of the fuzzy sets corresponding to each parameter.

Complement: For a fuzzy soft set (F, E)

$$F^c(e) = 1 - F(e) \quad \forall e \in E$$

This operation inverts the membership degrees for each parameter.

Mathematical Representations

Intersection

$$(F \cap G)(e) = F(e) \cap G(e) \quad \forall e \in E$$

Where F and G are fuzzy soft sets, and $F(e) \cap G(e)$ is the intersection of fuzzy sets corresponding to parameter e .

Union

$$(F \cup G)(e) = F(e) \cup G(e) \quad \forall e \in E$$

Where $F(e) \cup G(e)$ is the union of fuzzy sets corresponding to parameter e .

Complement:

$$F^c(e) = (F(e))^c \quad \forall e \in E$$

Where $(F(e))^c$ is the complement of the fuzzy set $F(e)$

Example**Fuzzy Soft Set Representation:**

Let $E = \{e_1, e_2\}$ be a set of parameters and

$U = \{u_1, u_2, u_3, u_4\}$ be the universal set.

If

$F(e_1) = \{(u_1, 0.7), (u_2, 0.4)\}$ and $F(e_2) = \{(u_3, 0.9), (u_4, 0.5)\}$,

then the fuzzy soft set F can be represented as:

$$F = \{(e_1, \{(u_1, 0.7), (u_2, 0.4)\}), (e_2, \{(u_3, 0.9), (u_4, 0.5)\})\}$$

Propositions

Let (F, A) be a fuzzy soft set. Then, the optimal choice function $f: U \rightarrow [0, 1]$ defined by $f(u_i) = \bigwedge_{a_j \in A} F(a_j)(u_i)$ is the best choice function, where \bigwedge denotes the minimum operator.

Proof

Let $u_i \in U$ be an alternative. The optimal choice function $f(u_i)$ represents the minimum degree of membership of the alternative u_i to all the criteria in A . This ensures that the alternative selected is the best compromise among all the criteria, as it satisfies all the criteria to the greatest extent possible.

Suppose we have a case scenario:

Consider a healthcare decision-making problem where the set of parameters is

$A = \{a_1, a_2, a_3\}$, representing "Symptom Severity", "Test Results", and "Patient Preference", respectively. The set of alternatives is $U = \{u_1, u_2, u_3, u_4\}$, representing different treatment options.

Proof

Construct the Fuzzy Soft Decision Matrix: Let's assume the following fuzzy soft decision matrix:

	u_1	u_2	u_3	u_4
a_1	0.8	0.6	0.7	0.5
a_2	0.7	0.8	0.6	0.7
a_3	0.6	0.7	0.8	0.6

The elements in the matrix represent the degree of membership of each alternative to the corresponding criterion.

Compute the Optimal Choice Function $f(u_i)$:

The optimal choice function $f(u_i)$ is defined as:

$$f(u_i) = \bigwedge_{a_j \in A} F(a_j)(u_i)$$

where \bigwedge denotes the minimum operator.

Applying this to our example:

$$f(u_1) = \min(0.8, 0.7, 0.6) = 0.6$$

$$f(u_2) = \min(0.6, 0.8, 0.7) = 0.6$$

$$f(u_3) = \min(0.7, 0.6, 0.8) = 0.6$$

$$f(u_4) = \min(0.5, 0.7, 0.6) = 0.5$$

Select the Optimal Decisions:

The alternatives with the maximum value of the optimal choice function are selected as the optimal decisions.

In this case, the maximum value of the optimal choice function is 0.6, and it is achieved by alternatives u_1 , u_2 , and u_3 .

Therefore, the optimal decisions are u_1 , u_2 , and u_3 .

Suppose we have another case scenario:

Considering a healthcare treatment decision-making problem where the set of parameters is $A = \{a_1, a_2, a_3, a_4\}$, representing "Effectiveness of Treatment", "Side Effects", "Cost of Treatment", and "Patient Preference", respectively. The set of alternatives (potential treatment options) is $U = \{u_1, u_2, u_3, u_4\}$.

Construct the Fuzzy Soft Decision Matrix:

Let's assume the following fuzzy soft decision matrix:

	u_1	u_2	u_3	u_4
a_1	0.8	0.7	0.6	0.7
a_2	0.7	0.8	0.6	0.7
a_3	0.6	0.7	0.8	0.6
a_4	0.7	0.6	0.7	0.8

The elements in the matrix represent the degree of membership of each alternative to the corresponding criterion.

Compute the Optimal Choice Function $f(u_i)$:

The optimal choice function $f(u_i)$ is defined as:

$$f(u_i) = \bigwedge_{a_j \in A} F(a_j)(u_i)$$

where \bigwedge denotes the minimum operator.

Applying this to our example:

$$f(u_1) = \min(0.8, 0.7, 0.6, 0.7) = 0.6$$

$$f(u_2) = \min(0.7, 0.8, 0.7, 0.6) = 0.6$$

$$f(u_3) = \min(0.6, 0.6, 0.8, 0.7) = 0.6$$

$$f(u_4) = \min(0.7, 0.7, 0.6, 0.8) = 0.6$$

Select the Optimal Decisions:

The alternatives with the maximum value of the optimal choice function are selected as the optimal decisions.

In this case, the maximum value of the optimal choice function is 0.6, and it is achieved by all four alternatives (u_1, u_2, u_3 , and u_4).

Therefore, the optimal decision(s) are u_1, u_2, u_3 , and u_4 .

Theorems

These theorems are properties which are important in understanding the algebraic structure of fuzzy soft sets and in developing efficient algorithms for manipulating and analyzing fuzzy soft set data.

Theorem 1: Idempotency of Union and Intersection

Let (F, A) and (G, B) be two fuzzy soft sets over the common universe U . Then, the following properties hold:

$$(F, A) \cup (F, A) = (F, A)$$

$$(F, A) \cap (F, A) = (F, A)$$

Theorem 2: Commutativity of Union and Intersection

Let (F, A) and (G, B) be two fuzzy soft sets over the common universe U . Then, the following properties hold:

$$(F, A) \cup (G, B) = (G, B) \cup (F, A)$$

$$(F, A) \cap (G, B) = (G, B) \cap (F, A)$$

Theorem 3: Associativity of Union and Intersection

Let $(F, A), (G, B)$, and (H, C) be three fuzzy soft sets over the common universe U . Then, the following properties hold:

$$((F, A) \cup (G, B)) \cup (H, C) = (F, A) \cup (G, B) \cup (H, C)$$

$$((F, A) \cap (G, B)) \cap (H, C) = (F, A) \cap (G, B) \cap (H, C)$$

Theorem 4: Distributivity of Union and Intersection

Let $(F, A), (G, B)$, and (H, C) be three fuzzy soft sets over the common universe U . Then, the following properties hold:

$$(F, A) \cup ((G, B) \cap (H, C)) = ((F, A) \cup (G, B)) \cap ((F, A) \cup (H, C))$$

$$(F, A) \cap ((G, B) \cup (H, C)) = ((F, A) \cap (G, B)) \cup ((F, A) \cap (H, C))$$

Theorem 5: Inclusion of Fuzzy Soft Sets

Let (F, A) and (G, B) be two fuzzy soft sets over the common universe U . Then, (F, A) is said to be a fuzzy soft subset of (G, B) , denoted as

$$(F, A) \subseteq (G, B), \text{ if: } A \subseteq B$$

$$\forall x \in U \text{ and } \forall a \in A, F(a)(x) \leq G(a)(x)$$

Mathematically, this can be represented as:

$$(F, A) \subseteq (G, B) \Leftrightarrow (A \subseteq B) \wedge (\forall x \in U, \forall a \in A, F(a)(x) \leq G(a)(x))$$

Theorem 6: Equality of Fuzzy Soft Sets

Two fuzzy soft sets (F, A) and (G, B) over the common universe U are said to be equal, denoted as $(F, A) = (G, B)$, if:

$$A = B$$

$$\forall x \in U \text{ and } \forall a \in A, F(a)(x) = G(a)(x)$$

Mathematically, this can be represented as:

$$(F, A) = (G, B) \Leftrightarrow (A = B) \wedge (\forall x \in U, \forall a \in A, F(a)(x) = G(a)(x))$$

Theorem 7: Complement of a Fuzzy Soft Set

The complement of a fuzzy soft set (F, A) over the universe U , denoted as $(F, A)^c$, is defined as:

$$(F, A)^c = (F^c, A)$$

where $F^c: A \rightarrow P(U)$ is a mapping defined by

$$F^c(a)(x) = 1 - F(a)(x) \quad \forall x \in U \text{ and } a \in A.$$

Mathematically, this can be represented as:

$$(F, A)^c = (F^c, A), \text{ where } F^c(a)(x) = 1 - F(a)(x), \forall x \in U, \forall a \in A$$

Theorem 8: De Morgan's Laws for Fuzzy Soft Sets

Let (F, A) and (G, B) be two fuzzy soft sets over the common universe U . Then, the following De Morgan's laws hold:

$$((F, A) \cup (G, B))^c = (F, A)^c \cap (G, B)^c$$

$$((F, A) \cap (G, B))^c = (F, A)^c \cup (G, B)^c$$

Mathematically, this can be represented as:

$$((F, A) \cup (G, B))^c = (F^c, A) \cap (G^c, B)$$

$$((F, A) \cap (G, B))^c = (F^c, A) \cup (G^c, B)$$

These theorems provide a deeper understanding of the properties and operations related to fuzzy soft sets, which are essential for their effective application in various decision-making and problem-solving scenarios.

ANSWERS TO RESEARCH QUESTIONS, TESTING OF HYPOTHESIS, MATHEMATICAL EXAMPLES & SUMMARY OF FINDINGS

Medical Diagnosis and Treatment Selection: Fuzzy soft sets aid in medical diagnosis and treatment selection by modeling the intricate connections between patient symptoms, test results, and possible diagnoses, thereby aiding in the selection of suitable treatment options.

Personalized Medicine and Precision Therapeutics: Fuzzy soft sets aid in personalized medicine and precision therapeutics by incorporating patient-specific factors, genetic information, and clinical data, enabling more effective healthcare interventions.

Health Resource Allocation and Management: Fuzzy soft sets aid in healthcare resource allocation and management by modeling complex relationships between resources, patient needs, and budget constraints, enabling efficient decision-making in resource distribution.

Clinical Decision Support Systems: Fuzzy soft set-based models can be integrated into clinical decision support systems to aid healthcare professionals in complex decision-making processes like medication management, surgical planning, and discharge planning.

Public Health Policy and Epidemiological Modeling: Fuzzy soft sets can be utilized in public health policy and epidemiological modeling to understand the

uncertainty and complexity of public health data, aiding in the development of more effective strategies.

Biomedical Data Analysis and Interpretation: Fuzzy soft sets can be effectively applied to the analysis of biomedical data, including genomic data, medical imaging, and electronic health records, to aid decision-making in areas like drug discovery and disease prevention within the healthcare sector.

Testing of Hypothesis**Hypothesis 1**

The key principles and concepts which are fundamental to fuzzy soft set theory and its application in healthcare decision-making scenarios can be hypothesized following:

Hypothesis

Fuzzy soft set theory is a method used in healthcare decision-making to represent uncertainty and imprecision in data and patient information. It allows for a more nuanced and flexible representation of elements' belongingness, compared to crisp set theory.

This approach also enables multidimensional decision-making, capturing complex factors in medical diagnosis, treatment planning, and resource allocation.

Fuzzy soft set theory can accommodate stakeholder preferences and priorities, allowing for personalized decision support. Its scalability allows it to be applied to various healthcare domains, from individual patient care to population-level decision-making.

The theory also provides transparency and interpretability, making it accessible to healthcare professionals and decision-makers, enhancing trust, facilitating collaborative decision-making, and enabling better understanding of the reasoning behind recommended actions.

Hypothesis 2

Fuzzy soft set theory can be effectively applied in the following healthcare decision-making scenarios:

Mathematical Examples

Let's consider some mathematical examples demonstrating the application of the fuzzy soft set theorems.

Example 1: Idempotency of Union and Intersection

Let's consider two fuzzy soft sets:

$$(F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3)\})\}$$

$$(F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3)\})\}$$

Applying Theorem 1:

$$(F, A) \cup (F, A) = (F, A)$$

$$(F, A) \cap (F, A) = (F, A)$$

The union and intersection of the fuzzy soft sets (F, A) with themselves result in the original fuzzy soft set (F, A) . This demonstrates the idempotency property.

Example 2: Commutativity of Union and Intersection

Let's consider two fuzzy soft sets:

$$(F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3)\})\}$$

$$(G, B) = \{(x, \{(d, 0.5), (e, 0.2), (f, 0.4)\}), (y, \{(d, 0.6), (e, 0.3), (f, 0.7)\})\}$$

Applying Theorem 2:

$$(F, A) \cup (G, B) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.5), (e, 0.2), (f, 0.4)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7)\})\}$$

$$(G, B) \cup (F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.5), (e, 0.2), (f, 0.4)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7)\})\}$$

The union and intersection of the fuzzy soft sets (F, A) and (G, B) are commutative, as shown by the identical results.

Example 3: Associativity of Union and Intersection

Let's consider three fuzzy soft sets:

$$(F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3)\})\}$$

$$(G, B) = \{(x, \{(d, 0.5), (e, 0.2), (f, 0.4)\}), (y, \{(d, 0.6), (e, 0.3), (f, 0.7)\})\}$$

$$(H, C) = \{(x, \{(g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

Applying Theorem 3:

$$((F, A) \cup (G, B)) \cup (H, C) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.5), (e, 0.2), (f, 0.4), (g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7), (g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

$$(F, A) \cup (G, B) \cup (H, C) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.5), (e, 0.2), (f, 0.4), (g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7), (g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

$$\{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7), (g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

The results of the union and intersection operations are the same, demonstrating the associativity property.

Example 4: Distributivity of Union and Intersection

Let's consider three fuzzy soft sets:

$$(F, A) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3)\})\}$$

$$(G, B) = \{(x, \{(d, 0.5), (e, 0.2), (f, 0.4)\}), (y, \{(d, 0.6), (e, 0.3), (f, 0.7)\})\}$$

$$(H, C) = \{(x, \{(g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

Applying Theorem 4:

$$(F, A) \cup ((G, B) \cap (H, C)) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.3), (e, 0.2), (f, 0.2), (g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.4), (e, 0.3), (f, 0.4), (g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

$$((F, A) \cup (G, B)) \cap ((F, A) \cup (H, C)) = \{(x, \{(a, 0.7), (b, 0.4), (c, 0.6), (d, 0.5), (e, 0.2), (f, 0.4), (g, 0.3), (h, 0.6), (i, 0.2)\}), (y, \{(a, 0.8), (b, 0.5), (c, 0.3), (d, 0.6), (e, 0.3), (f, 0.7), (g, 0.4), (h, 0.7), (i, 0.1)\})\}$$

The results of the two expressions are the same, demonstrating the distributivity property.

Example 5: Another example using De Morgan's Laws for Fuzzy Soft Sets to address a different health-related issue.

Suppose we have a fuzzy soft set (F, A) that represents the risk factors for developing a certain type of cancer. The universe U represents the set of patients, and the parameter set A contains attributes like "family history", "smoking", "obesity", and "lack of physical activity".

We want to determine the patients who are not at risk for developing this type of cancer. To do this, we can use Theorem 8: De Morgan's Laws for Fuzzy Soft Sets.

Solution

Let's consider the following fuzzy soft set (F, A) :

$$U = \{p_1, p_2, p_3, p_4, p_5\}$$

$$A = \{\text{"family history"}, \text{"smoking"}, \text{"obesity"}, \text{"lack of physical activity"}\}$$

The membership values of the patients for each risk factor are given in the following table:

Patients	Family History	Smoking	Obesity	Lack of Physical Activity
p_1	0.7	0.8	0.6	0.5
p_2	0.5	0.6	0.7	0.4
p_3	0.3	0.4	0.5	0.3
p_4	0.6	0.7	0.6	0.8
p_5	0.4	0.5	0.4	0.6

Step 1: Define the complement of the fuzzy soft set (F, A) .

Let $(F, A)^c = (\tilde{F}, A)$ be the complement of the fuzzy soft set (F, A) .

Step 2: Apply the first part of Theorem 8 to find the negation of the fuzzy soft set (F, A) $(F, A) = (\tilde{F}, A)$

The negation of the fuzzy soft set (F, A) , which is (\tilde{F}, A) , represents the patients who are not at risk for developing the cancer.

For the membership values for patient p_1 in the negation of the fuzzy soft set (F, A) would be:

Family History: $1 - 0.7 = 0.3$

Smoking: $1 - 0.8 = 0.2$

Obesity: $1 - 0.6 = 0.4$

Lack of Physical Activity: $1 - 0.5 = 0.5$

We can then do same to get for the membership values for patient p_2, p_3, p_4 , and p_5 .

From Theorem 8, De Morgan's laws can help healthcare providers identify patients not at risk for cancer, enabling targeted prevention and management strategies, focusing on at-risk patients and tailoring interventions accordingly.

Summary of the Findings

The study reveals that fuzzy soft set theory can be effectively applied in various healthcare decision-making scenarios, including diagnostic support systems, treatment planning, resource allocation, and patient-centered care.

A methodology for applying fuzzy soft set theory to healthcare decision-making scenarios involves identifying scenarios, constructing fuzzy soft set models, developing decision-making algorithms, validating and implementing the methodology, and refining and enhancing the methodology.

DISCUSSION, CONCLUSION AND RECOMMENDATIONS

Discussion of the Findings

This study explores the application of fuzzy soft set theory in healthcare decision-making scenarios. It focuses on diagnostic support systems, treatment planning, resource allocation, and patient-centered care.

Fuzzy soft set theory can help healthcare professionals make more accurate diagnoses by modeling the uncertain and imprecise nature of symptoms, test results, and patient information. This approach is particularly relevant in the healthcare sector, where dealing with uncertain and incomplete information is a common challenge. The study also highlights the importance of fuzzy soft sets in addressing the complexities and uncertainties inherent in healthcare decisions.

Fuzzy soft set theory can be applied to treatment planning and optimization, allowing healthcare professionals to navigate complex trade-offs and uncertainties. It can also be used in resource allocation and prioritization decisions, such as the distribution of medical equipment, staff scheduling, and budget allocation. The study also highlights the potential of fuzzy soft set theory in facilitating collaborative decision-making and enhancing patient engagement in healthcare.

In conclusion, the study highlights the significant potential of fuzzy soft set theory in addressing the complexities and uncertainties inherent in healthcare decision-making scenarios. By incorporating this flexible and multidimensional framework, healthcare professionals can enhance their decision-making capabilities, optimize resource utilization, and improve patient-centered care.

Implications of the Study

Describing the Practical Involvements of my Study

The fuzzy soft set theory can significantly enhance healthcare decision-making by capturing uncertainty

and imprecision in medical data, leading to more accurate and personalized diagnostic support systems. This approach can develop robust treatment planning models that account for multiple clinical factors and patient preferences. It can also enhance resource allocation and prioritization, ensuring equitable utilization of limited healthcare resources. It promotes personalized and patient-centered care by integrating patient-specific factors into the decision-making process. Implementing fuzzy soft set-based decision support systems can help healthcare professionals navigate the complex healthcare landscape, providing valuable insights and recommendations.

Advantages and Disadvantages

Advantages

Fuzzy soft sets are a decision support method that manages uncertainty in healthcare data, integrating diverse stakeholder inputs for comprehensive, inclusive decision-making. They support personalized treatment plans, considering individual patient characteristics and preferences, and enhance transparency, fostering trust and engagement between patients and healthcare professionals.

Disadvantages

Fuzzy soft sets in healthcare pose challenges due to their complexity, data quality, and ethical concerns. Adopting these systems may be difficult for healthcare professionals without technical expertise. Ensuring data reliability is crucial, and integrating them may require significant organizational changes and training. Lack of standardized frameworks may cause inconsistencies in decision-making.

Usefulness and Benefits

Fuzzy soft sets can improve diagnostic accuracy and treatment planning by considering clinical and patient-specific factors.

They can also optimize resource allocation in healthcare by distributing scarce resources like hospital beds and medical equipment.

Fuzzy soft sets can also enhance public health decision-making by considering stakeholder perspectives and socioeconomic factors.

They can also enable personalized and patient-centric care, tailored to individual patient needs and preferences.

Overall, fuzzy soft sets offer numerous benefits in healthcare.

CONCLUSION

The study explores the application of fuzzy soft set theory in healthcare decision-making scenarios. It suggests that this mathematical framework can effectively address the complexities and uncertainties in healthcare-related decisions. The methodology involves identifying key decision-making scenarios, constructing appropriate fuzzy soft set models, and developing decision-making algorithms based on fuzzy soft set operations. The study emphasizes the importance of implementation, validation, and continuous refinement to ensure the effectiveness of fuzzy soft set-based decision support systems. The practical implications include improved medical diagnosis, treatment planning, resource allocation, patient-centered care, and knowledge management. The study concludes that applying fuzzy soft set theory to healthcare decision-making can unlock new opportunities for improved diagnostic accuracy, resource allocation, and patient-centered care.

RECOMMENDATIONS

Fuzzy soft sets can be integrated with advanced techniques like machine learning algorithms and multi-criteria decision analysis (MCDA) to improve predictive capabilities and adaptability in decision support systems. They can also be used to develop intelligent clinical decision support systems that continuously improve recommendations based on evolving patient data and medical knowledge. Fuzzy soft sets can also be used to capture healthcare professionals' experiences and expertise, enabling personalized and context-aware decision support. They can also support real-time decision-making in time-critical healthcare scenarios. Fuzzy soft sets can also be applied to emerging healthcare domains like telehealth, remote patient monitoring, digital therapeutics, and healthcare supply chain optimization. To promote their use, researchers should conduct comprehensive research, facilitate case studies, and develop guidelines and frameworks.

FUTURE PROSPECT

The study on fuzzy soft set theory in healthcare decision-making suggests several potential areas for further research and development. These include expanding application domains, integrating emerging

technologies, enhancing personalized and precision healthcare, addressing complex, multidimensional decision-making scenarios, modeling and quantifying uncertainties, enhancing collaborative decision-making and knowledge management, and addressing ethical and regulatory considerations. The framework could be applied to medical diagnosis, treatment planning, resource allocation, patient-centered care, medication management, healthcare facility planning, public health policy, and telemedicine. The integration of artificial intelligence, machine learning, and big data analytics could enhance the capabilities of healthcare decision support systems. The study also suggests integrating fuzzy soft set theory with knowledge management platforms to facilitate the sharing of best practices and lessons learned. These efforts could lead to more accurate, personalized, and effective decision-making processes, ultimately improving patient outcomes and the healthcare system.

REFERENCES

- [1] Çağman N, Enginoğlu S, Çıtak F. Fuzzy soft set theory and its applications. *Iranian Journal of Fuzzy Systems* 2011; 8(3): 137-147.
- [2] Masic I. Medical decision making - An overview. *Acta Informatica Medica* 2022; 30(3): 230-235. <https://doi.org/10.5455/aim.2022.30.230-235>
- [3] Alkhazaleh S. Effective fuzzy soft set theory and its applications. *Applied Computational Intelligence and Soft Computing* 2022; 2022: 1-12. <https://doi.org/10.1155/2022/6469745>
- [4] The Investopedia Team. Healthcare sector. Investopedia 2021. https://www.investopedia.com/terms/h/health_care_sector.asp
- [5] University of Massachusetts Dartmouth. Decision-making process. UMass Dartmouth 2021. <https://www.umassd.edu/fycm/decision-making/process/>
- [6] Zadeh LA. Fuzzy sets. *Information and Control* 1965; 8(3): 338-353. [https://doi.org/10.1016/S0019-9958\(65\)90241-X](https://doi.org/10.1016/S0019-9958(65)90241-X)
- [7] Molodtsov DA. Soft set theory—First results. *Computers & Mathematics with Applications* 1999; 37(4-5): 19-31. [https://doi.org/10.1016/S0898-1221\(99\)0006-5](https://doi.org/10.1016/S0898-1221(99)0006-5)
- [8] Maji PK, Biswas R, Roy AR. Fuzzy soft sets. *Journal of Fuzzy Mathematics* 2001; 9(3): 589-602.
- [9] Deli I, Çağman N. Intuitionistic fuzzy parameterized soft set theory and its decision making. *Applied Soft Computing* 2015; 28: 109-113. <https://doi.org/10.1016/j.asoc.2014.11.053>
- [10] Alharthi HS, Khalifa AH. A combined fuzzy soft set and TOPSIS approach for medical diagnosis. *Applied Soft Computing* 2021; 98: 106825.
- [11] Gong Z, Liu P. Fuzzy soft set approach to group decision making under fuzzy environment. *Journal of Information & Computational Science* 2011; 8(9): 1649-1658.
- [12] Chen D, Tang X. The application of soft sets in medical diagnosis. *Journal of King Saud University - Computer and Information Sciences* 2007; 19(1): 117-129.
- [13] Kong Z, Yang Y. Fuzzy soft sets and fuzzy soft set theory. *Computers & Mathematics with Applications* 2008; 56(12): 3032-3045. <https://doi.org/10.1016/j.camwa.2008.07.013>
- [14] Ali M, Feng F, Liu X, Min WK, Shabir M. On some new operations in soft set theory. *Computers & Mathematics with Applications* 2009; 57(9): 1547-1553. <https://doi.org/10.1016/j.camwa.2008.11.009>
- [15] Maji PK, Biswas R, Roy AR. Intuitionistic fuzzy soft sets for medical diagnosis 2003.
- [16] Sanchez E. Inverses of fuzzy relations. Application to possibility distributions and medical diagnosis. *Fuzzy Sets and Systems* 1979; 2(1): 75-86. [https://doi.org/10.1016/0165-0114\(79\)90017-4](https://doi.org/10.1016/0165-0114(79)90017-4)
- [17] Prade H, Testemale C. Generalized fuzzy-event variables and their applications in decision-making. *IEEE Transactions on Systems, Man, and Cybernetics* 1984; 14(1): 61-69.
- [18] Bezdek JC, Ehrlich R, Full W. FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences* 1984; 10(2-3): 191-203. [https://doi.org/10.1016/0098-3004\(84\)90020-7](https://doi.org/10.1016/0098-3004(84)90020-7)
- [19] Kickert WJ, Mamdani EH. Analysis of a fuzzy logic controller. *Fuzzy Sets and Systems* 1978; 1(1): 29-44. [https://doi.org/10.1016/0165-0114\(78\)90030-1](https://doi.org/10.1016/0165-0114(78)90030-1)
- [20] Feng F, Liu X, Leoreanu-Fotea V, Jun YB. Soft sets and soft rough sets. *Information Sciences* 2011; 181(6): 1125-1137. <https://doi.org/10.1016/j.ins.2010.11.004>
- [21] Alcantud JCR. A novel algorithm for fuzzy soft set based decision making from multiobserver data. *Information Fusion* 2016; 29: 142-148. <https://doi.org/10.1016/j.inffus.2015.08.007>
- [22] Zhan J, Alcantud JCR, Khan MS. A survey on recent decision making methods using fuzzy soft sets. *Expert Systems with Applications* 2020; 150: 113321.
- [23] Khan MS, Chatterjee A, Pal M. Medical decision support system based on fuzzy soft set theory. *Journal of Intelligent & Fuzzy Systems* 2020; 38(2): 1919-1929. <https://doi.org/10.3233/JIFS-190944>
- [24] Garg H, Arora R, Janisaram R. Qualitative flexible inventory model for deteriorating items with fuzzy soft set approach. *Expert Systems with Applications* 2020; 142: 113016.
- [25] Chatterjee A, Pal M. A new approach to medical diagnosis using soft set and fuzzy soft set. *Journal of Intelligent & Fuzzy Systems* 2021; 40(1): 1245-1258.