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Neutrosophic Binary Relation Matrices for Enhanced Medical Diagnosis

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Abstract

Medical diagnosis often relies on intricate relationships between symptoms, diseases, and patient data. Traditional methods struggle to account for the inherent uncertainties and indeterminacies within this process. This paper proposes the application of Neutrosophic Binary Relation Matrices (NBRMs) for enhanced uncertainty management in medical diagnosis. NBRMs offer a novel framework by incorporating truth (T), indeterminacy (I), and falsity (F) degrees to represent these relationships. We explore the mathematical structure of NBRMs and discuss their potential in modeling complex symptom-disease associations, incorporating individual patient factors, and developing more nuanced decision support systems. By leveraging NBRMs, we can potentially improve diagnostic accuracy and navigate the complexities of medical data. This paper paves the way for further research on utilizing neutrosophic logic to enhance medical diagnosis and contribute to more informed healthcare decisions.

Keywords: Neutrosophic Sets; Neutrosophic Binary Relation Matrices; Medical Diagnosis; Uncertainty Management; Fuzzy Logic; Decision Support Systems; Patient Data Analysis; Personalized Medicine.

1 | Introduction

Medical diagnosis, the cornerstone of healthcare, involves identifying the underlying cause of a patient's condition based on symptoms, medical history, and various tests [17]. Traditionally, this process relies on establishing relationships between observed symptoms and potential diseases. These relationships are often modeled using classical binary relations, which represent a clear connection between two sets [1]. However, classical binary relations have limitations when applied to medical diagnosis [10].

Classical binary relations define a relationship between two sets (e.g., symptoms and diseases) as either true (1) or false (0) [7]. This binary nature fails to capture the inherent uncertainty present in medical scenarios. Here is why:

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- Uncertainty in Symptoms: Symptoms can vary in intensity, presentation, and manifestation. A single symptom might not definitively point to a specific disease [13].
- Incomplete Information: Medical data can be incomplete due to limitations in diagnostic tests or individual patient factors like allergies or medications [11,12].
- Comorbidities: Patients often have multiple co-existing conditions, making it challenging to pinpoint a single cause based solely on a binary relationship [13,14].

These limitations can lead to misdiagnosis or delayed diagnosis, highlighting the need for a more nuanced approach to representing relationships in medical diagnosis.

Neutrosophic Sets, introduced by Smarandache [2-4], offer a powerful tool for representing uncertainty. They extend classical sets by incorporating three truth membership degrees [19]:

- Truth (T): The degree to which an element belongs to the set [9].
- Indeterminacy (I): The degree to which the element is belonging is indeterminate or unknown [9].
- Falsity (F): The degree to which an element does not belong to the set [9].

These degrees can range from 0 to 1, allowing for a richer representation of the relationship between elements [5,6].

The advantage of Neutrosophic Sets lies in their ability to capture the "in-between" states often encountered in medical diagnosis. They can represent the possibility of a symptom being both indicative of a disease (T) and inconclusive (I) at the same time [9].

Neutrosophic Binary Relation Matrices (NBRMs) leverage the capabilities of Neutrosophic Sets to represent relationships between two sets [8,9]. An NBRM is a matrix where each entry represents the degree of truth (T), indeterminacy (I), and falsity (F) associated with the relationship between a specific element in the first set and an element in the second set.

This allows for a more nuanced representation of complex relationships in medical diagnosis. For Application, an NBRM could indicate that a specific symptom has a high degree of truth (T) in associating with a particular disease but also possesses a degree of indeterminacy (I) due to the presence of other potential causes [15-18].

In essence, NBRMs offer a promising framework for capturing the complexities of medical diagnosis, paving the way for a more accurate and data-driven approach to healthcare decision-making [16]. There are many medical and engineering applications using the neutrosophic theory, as mentioned in the references [20-28].

2 | Background

Despite its crucial role in healthcare, medical diagnosis remains a complex task. Traditional approaches often rely on establishing clear-cut relationships between symptoms and diseases. However, these methods have limitations when dealing with the inherent uncertainties present in real-world scenarios.

2.1 | Existing Methods and Their Limitations

- Clinical Decision Support Systems (CDSS): These systems assist healthcare professionals by providing recommendations based on predefined rules and existing data. However, CDSS can be limited by rigid rule sets and lacks the flexibility to handle unique patient presentations.
- Statistical Analysis: Statistical methods help analyze large datasets to identify trends and associations between symptoms and diseases. However, these methods may struggle with limited data, individual patient variations, and the challenge of establishing causality.

- Expert Systems: These systems mimic the knowledge and reasoning of human experts. While valuable, they rely on pre-programmed knowledge and may not adapt well to new medical discoveries or atypical patient cases.

These existing methods often struggle with the inherent complexities of medical diagnosis, including:

- Uncertainty in symptom presentation: Symptoms can vary in intensity and may manifest differently in different individuals.
- Incomplete data: Diagnostic tests may have limitations, and patient history can be incomplete.
- Comorbidities: Patients with multiple co-existing conditions can present with a confusing constellation of symptoms.

2.2 | Fuzzy Logic and Fuzzy Relational Databases: Embracing Vagueness

Fuzzy logic emerged as a way to model uncertainty in situations where a clear yes or no answer might not be possible. It utilizes fuzzy sets, where membership degrees range from 0 (completely not belonging) to 1 (completely belonging). This allows for a more nuanced representation of relationships, acknowledging the "in-between" states.

Fuzzy relational databases extend these concepts by storing fuzzy relationships between entities. They have found applications in medical diagnosis, allowing for the modeling of imprecise symptoms or the relative likelihood of a disease based on various factors.

2.3 | Fuzzy Logic vs. Neutrosophic Logic: Refining Uncertainty Management

While fuzzy logic was a significant step forward, neutrosophic logic offers additional capabilities for capturing uncertainty in medical diagnosis. Here is a comparison as presented in Table 1:

Table 1. Fuzzy logic vs. neutrosophic logic.

Feature	Fuzzy Logic	Neutrosophic Logic
Membership Degrees	Two: Truth (0-1)	Three: Truth (T), Indeterminacy (I), Falsity (F) (0-1)
Handling Indeterminacy	Represented by "partially true" or intermediate values	Explicitly represented by the "Indeterminacy" degree (I)
Strengths	More nuanced than classical sets	Captures uncertainty beyond simple truth/falsehood
Limitations	Limited ability to distinguish between "don't know" and "not true"	Requires more complex computations

Neutrosophic sets offer a significant benefit by explicitly addressing indeterminacy through the "I" degree. This allows for a more accurate representation of situations where a symptom is neither definitively indicative nor definitively non-indicative of a disease. This additional dimension provides a richer framework for modeling the complexities of medical diagnosis.

3 | Neutrosophic Binary Relation Matrices

Neutrosophic Binary Relation Matrices (NBRMs) provide a powerful tool for representing relationships in medical diagnosis by incorporating uncertainty through neutrosophic logic. Let us delve into their structure, application, and relevant operations.

3.1 | Mathematical Structure of Neutrosophic Binary Relation Matrices

Neutrosophic Binary Relation Matrices (NBRMs) offer a mathematical framework for representing relationships between elements in two sets, incorporating uncertainty through neutrosophic logic. Here is a breakdown of their structure:

Sets:

- An NBRM involves two sets:
  - Row Set (R): This set represents the elements in the first category (e.g., Symptoms).
  - Column Set (C): This set represents the elements in the second category (e.g., Diseases).

Matrix Representation:

- The NBRM is represented by a matrix with dimensions $|R|$ x $|C|$, where:
  - $|R|$ is the number of elements in the Row Set.
  - $|C|$ is the number of elements in the Column Set.
- Each entry in the matrix corresponds to the relationship between a specific element from the Row Set and an element from the Column Set.

Values in the Matrix:

- Unlike classical binary relations (0 or 1), NBRMs utilize three truth membership degrees (0 to 1) associated with neutrosophic logic:
  - Truth (T): This degree (Tij) represents the extent to which element i from the Row Set is related to element j from the Column Set. ($0 \leq Tij \leq 1$).
  - Indeterminacy (I): This degree (Iij) represents the uncertainty associated with the relationship between element i and element j. ($0 \leq Iij \leq 1$).
  - Falsity (F): This degree (Fij) represents the extent to which element i and element j are not related. ($0 \leq Fij \leq 1$)

Normalization Condition:

- The sum of Truth (T), Indeterminacy (I), and Falsity (F) for each entry (i, j) must satisfy the following condition: $Tij + Iij + Fij = 1$.

This ensures that all three degrees contribute to a complete picture of the relationship between elements.

Example:

Consider an NBRM representing the relationship between symptoms (Row Set) and diseases (Column Set). The matrix entry for "Fever" (Symptom) and "Flu" (Disease) might be:

(Tij, Iij, Fij) = (0.8, 0.1, 0.1)

This indicates:

- There is a high Value (0.8) suggesting fever is strongly indicative of flu.
- A low Indeterminacy (0.1) implies some certainty in the association.
- A low Falsity (0.1) suggests a low possibility that the fever is unrelated to the flu.

3.2 | Operations on NBRMs: Negation, Union, Intersection, and Complement for Advanced Analysis

NBRMs offer a richer framework for analyzing relationships compared to classical binary relations by allowing operations that consider the Truth (T), Indeterminacy (I), and Falsity (F) degrees. Here are some key operations on NBRMs:

1. Negation:

   - Negation flips the truth values (T) in an NBRM, essentially inverting the relationship between elements.

     Negation Operator (Neg): Neg(Tij) = 1 – Tij

     Example: If an NBRM entry for "Headache" and "Migraine" is (0.7, 0.2, 0.1), indicating a strong association, then the negation would be (0.3, 0.2, 0.7), suggesting a low likelihood of migraine given a headache.

2. Union:

   - Union combines two NBRMs with the same dimensions, element-wise. The resulting T, I, and F values represent the "maximum possibility" scenario.

     Union Operator (U): U (Tij, Tij') = max (Tij, Tij') U (Iij, Iij') = max (Iij, Iij') U (Fij, Fij') = max (Fij, Fij')

     Example: Consider two NBRMs representing the relationship between "Fatigue" and two different diseases (Disease A and Disease B). The union can help identify the overall likelihood of fatigue being associated with either disease.

3. Intersection:

   - Intersection combines two NBRMs with the same dimensions, element-wise. The resulting T, I, and F values represent the "minimum possibility" scenario.

     Intersection Operator (∩): ∩ (Tij, Tij') = min (Tij, Tij') ∩ (Iij, Iij') = min (Iij, Iij') ∩ (Fij, Fij') = min (Fij, Fij')

     Example: Intersection can be used to find symptoms consistently associated with a specific disease across different NBRMs based on various studies or patient data.

4. Complement:

   Complement calculates the "degree to which a relationship does not exist" for each entry in an NBRM.

   Complement Operator (Comp): Comp (Tij) = 1 - Tij Comp (Iij) = Iij (Indeterminacy remains unchanged) Comp (Fij) = Fij (Falsity remains unchanged).

   Example: The complement of the "Fever" and "Flu" examples (Tij = 0.8, Iij = 0.1, Fij = 0.1) would be (0.2, 0.1, 0.1). This indicates a low likelihood (0.2) that fever is unrelated to flu, while the indeterminacy and falsity remain the same.

   These operations allow for more nuanced analysis compared to classical binary relations. By considering the interplay between Truth, Indeterminacy, and Falsity, NBRMs offer a powerful tool for:

   - Ranking Relationships: Ordering elements based on the combined strength of their truth values across different NBRMs.

- Identifying Uncertainties: Highlighting entries with significant indeterminacy, prompting further investigation.
- Modeling Complexities: Capturing the "in-between" states often encountered in real-world scenarios.
- Properties of NBRMs:
    - T, I, and F are independent values, meaning a high truth value (T) does not necessarily imply low Indeterminacy (I) or Falsity (F).
    - $T + I + F \leq 1$. This ensures that all three degrees together represent the complete picture of the relationship.

While these are some core operations, NBRMs can be further extended with more complex calculations depending on the specific application. The ability to perform these operations opens doors for sophisticated analyses and decision-making processes that consider uncertainty in a more comprehensive way.

3.3 | Some Application

- Application 1: NBRM for Medical Diagnosis

Consider a patient presenting with a fever (Symptom 1) and a cough (Symptom 2). We want to represent the relationship between these symptoms and two potential diseases: the Flu (Disease 1) and Pneumonia (Disease 2) using an NBRM.

Sets:

- Row Set (Symptoms): {Fever (Symptom 1), Cough (Symptom 2)}.
- Column Set (Diseases): {Flu (Disease 1), Pneumonia (Disease 2)}.

Neutrosophic Binary Relation Matrix:

Table 2-1. NBRM for symptom-disease relationships.

	Flu (Disease 1)	**Pneumonia (Disease 2)**
Fever (Symptom 1)	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)
Cough (Symptom 2)	(0.7, 0.2, 0.1)	(0.6, 0.2, 0.2)

Table 2-2. NBRM for symptom-disease relationships.

	Disease 1 - Truth	**Disease 1 - Indeterminacy**	**Disease 1 - Falsity**	**Disease 2 - Truth**	**Disease 2 - Indeterminacy**	**Disease 2 - Falsity**
Fever (Symptom 1)	0.8	0.1	0.1	0.5	0.3	0.2
Cough (Symptom 2)	0.7	0.2	0.1	0.6	0.2	0.2

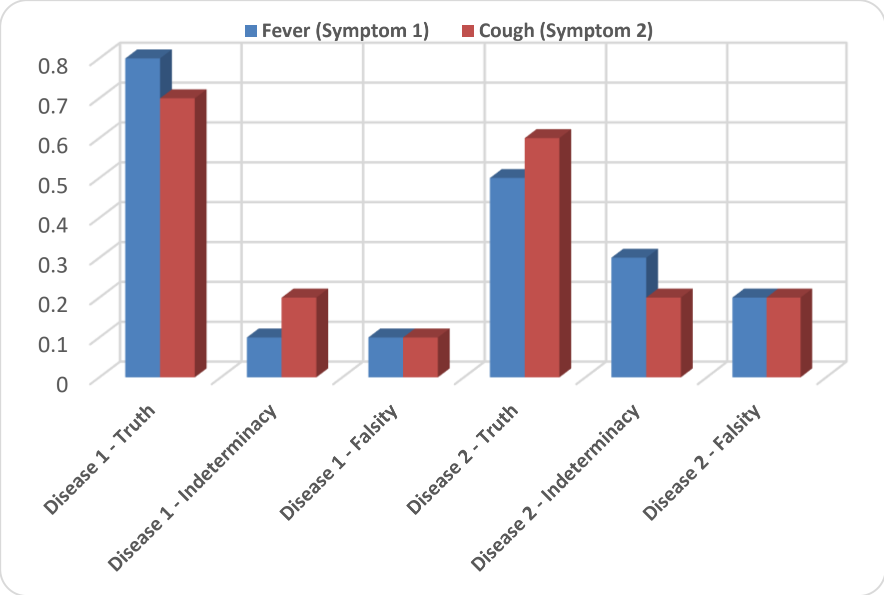

Figure 1. NBRM visualization: truth, indeterminacy, and falsity degrees for symptom-disease relationships.

Explanation of Values:

- Fever (Symptom 1) & Flu (Disease 1):
  - Truth (T) = 0.8: There is a high likelihood (0.8) that a fever is associated with the Flu.
  - Indeterminacy (I) = 0.1: There is a low degree of uncertainty (0.1) about this association. This could be due to the possibility of other causes of fever.
  - Falsity (F) = 0.1: There is a low possibility (0.1) that a fever is unrelated to the Flu.
- Fever (Symptom 1) & Pneumonia (Disease 2):
  - Truth (T) = 0.5: There is a moderate likelihood (0.5) that a fever is associated with Pneumonia.
  - Indeterminacy (I) = 0.3: There is a moderate degree of uncertainty (0.3) about this association. This could be due to other potential causes of fever or limitations in differentiating Flu from Pneumonia.
  - Falsity (F) = 0.2: There is a low-to-moderate possibility (0.2) that a fever is unrelated to Pneumonia.
- Cough (Symptom 2) & Flu (Disease 1):
  - Truth (T) = 0.7: There is a high likelihood (0.7) that a cough is associated with the Flu.
  - Indeterminacy (I) = 0.2: There is a moderate degree of uncertainty (0.2) about this association. This could be due to other respiratory illnesses causing cough.
  - Falsity (F) = 0.1: There is a low possibility (0.1) that a cough is unrelated to the Flu.
- Cough (Symptom 2) & Pneumonia (Disease 2):
  - Truth (T) = 0.6: There is a moderate-to-high likelihood (0.6) that a cough is associated with Pneumonia.
  - Indeterminacy (I) = 0.2: There is a moderate degree of uncertainty (0.2) about this association. This could be due to other respiratory illnesses causing cough.

  - Falsity (F) = 0.2: There is a low-to-moderate possibility (0.2) that a cough is unrelated to Pneumonia.

This NBRM provides a more nuanced picture compared to a binary approach. It highlights the high likelihood of both fever and cough being associated with the Flu but also acknowledges some degree of uncertainty due to other potential causes. Similarly, it indicates a moderate association between these symptoms and Pneumonia, reflecting the need for further investigation.

3.4 | Representing Relationships in Medical Diagnosis

NBRMs offer a nuanced way to represent relationships between symptoms, diseases, and patient data. Here is how:

- Symptoms and Diseases: The rows of an NBRM could represent symptoms, and the columns could represent diseases. Each entry (T, I, F) would then indicate the likelihood (T), uncertainty (I), and unlikelihood (F) of a specific symptom being associated with a particular disease.

A patient presents with two main symptoms: Chest pain (Symptom 1) and Shortness of Breath (Symptom 2). We want to represent the association between these symptoms and two potential diagnoses: Heart Attack (Disease 1) and Anxiety Attack (Disease 2) using an NBRM.

Sets:

- Row Set (Symptoms): {Chest Pain (Symptom 1), Shortness of Breath (Symptom 2)}.
- Column Set (Diseases): {Heart Attack (Disease 1), Anxiety Attack (Disease 2)}.

Neutrosophic Binary Relation Matrix:

Table 3-1. Association between symptoms and potential diagnoses using neutrosophic logic.

	Heart Attack (Disease 1)	**Anxiety Attack (Disease 2)**
Chest Pain (Symptom 1)	(0.7, 0.2, 0.1)	(0.3, 0.4, 0.3)
Shortness of Breath (Symptom 2)	(0.5, 0.3, 0.2)	(0.6, 0.2, 0.2)

Table 3-2. NBRM for symptom-disease relationships.

Symptoms	Heart Attack (Disease 1) T	Heart Attack (Disease 1) I	Heart Attack (Disease 1) F	Anxiety Attack (Disease 2) T	Anxiety Attack (Disease 2) I	Anxiety Attack (Disease 2) F
Chest Pain (Symptom 1)	0.7	0.2	0.1	0.3	0.4	0.3
Shortness of Breath (Symptom 2)	0.5	0.3	0.2	0.6	0.2	0.2

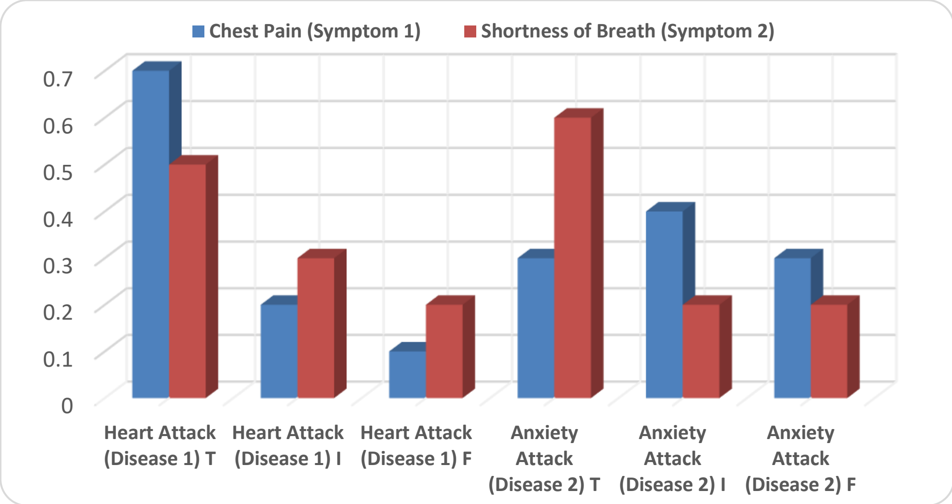

Figure 2. Neutrosophic representation of symptom-diagnosis associations.

Explanation of Values:

- Chest Pain (Symptom 1) & Heart Attack (Disease 1):
  - Truth (T) = 0.7: There is a high likelihood (0.7) that chest pain is a symptom associated with a heart attack.
  - Indeterminacy (I) = 0.2: There is a moderate degree of uncertainty (0.2) about this association. This could be due to other causes of chest pain, such as muscle strain or indigestion.
  - Falsity (F) = 0.1: There is a low possibility (0.1) that chest pain is unrelated to a heart attack.
- Chest Pain (Symptom 1) & Anxiety Attack (Disease 2):
  - Truth (T) = 0.3: There is a moderate likelihood (0.3) that chest pain can occur during an anxiety attack.
  - Indeterminacy (I) = 0.4: There is a high degree of uncertainty (0.4) about this association. Anxiety attacks can manifest in various ways, and chest pain might not always be a prominent symptom.
  - Falsity (F) = 0.3: There is a moderate possibility (0.3) that chest pain is unrelated to an anxiety attack.
- Shortness of Breath (Symptom 2) & Heart Attack (Disease 1):
  - Truth (T) = 0.5: There is a moderate likelihood (0.5) that shortness of breath is associated with a heart attack.
  - Indeterminacy (I) = 0.3: There is a moderate degree of uncertainty (0.3) about this association. Shortness of breath can also occur due to other factors like asthma or exertion.
  - Falsity (F) = 0.2: There is a low-to-moderate possibility (0.2) that shortness of breath is unrelated to a heart attack.
- Shortness of Breath (Symptom 2) & Anxiety Attack (Disease 2):
  - Truth (T) = 0.6: There is a high likelihood (0.6) that shortness of breath can occur during an anxiety attack.

  - Indeterminacy (I) = 0.2: There is a moderate degree of uncertainty (0.2) about this association. The severity of shortness of breath can vary in anxiety attacks.
  - Falsity (F) = 0.2: There is a low-to-moderate possibility (0.2) that shortness of breath is unrelated to an anxiety attack.

This NBRM demonstrates the advantage of incorporating uncertainty. While both symptoms have a higher association with a heart attack compared to an anxiety attack, the I (Indeterminacy) values highlight the need for further investigation due to potential overlap with other conditions. This allows healthcare professionals to consider a broader range of possibilities and make more informed decisions while prioritizing potentially life-threatening conditions like a heart attack.

- Patient Data Integration: NBRMs can be expanded to include additional rows or columns to incorporate patient-specific factors like age, medical history, or allergies. The corresponding T, I, and F values would reflect how these factors influence the relationship between symptoms and diseases for a particular patient.

  This flexibility allows NBRMs to capture the complexities of medical diagnosis, where symptoms can have varying degrees of association with diseases, and individual patient factors can influence the overall picture.

3.5 | NBRM Analysis: Chest Pain & Fatigue with Age & High Cholesterol for Heart Attack vs. Chronic Fatigue Syndrome

A 55-year-old male patient presents with chest pain (Symptom 1) and fatigue (Symptom 2). We want to represent the association between these symptoms and potential diagnoses (Heart Attack (Disease 1) and Chronic Fatigue Syndrome (Disease 2)) using an NBRM, considering the patient's age (55 years old) and a history of high cholesterol (Medical History).

Sets:

- Row Set (Symptoms & Patient Data): {Chest Pain (Symptom 1), Fatigue (Symptom 2), Age (55 years old), History of High Cholesterol (Medical History)}.
- Column Set (Diseases): {Heart Attack (Disease 1), Chronic Fatigue Syndrome (Disease 2)}.

Neutrosophic Binary Relation Matrix:

Table 4-1. Neutrosophic association between symptoms, patient data, and potential diagnoses.

Symptoms	Heart Attack (Disease 1)	Chronic Fatigue Syndrome (Disease 2)
Chest Pain (Symptom 1)	(0.7, 0.2, 0.1)	(0.2, 0.5, 0.3)
Fatigue (Symptom 2)	(0.4, 0.3, 0.3)	(0.7, 0.2, 0.1)
Age (55 years old)	(0.8, 0.1, 0.1)	(0.3, 0.4, 0.3)
High Cholesterol (MH)	(0.6, 0.2, 0.2)	(0.2, 0.5, 0.3)

Table 4-2. NBRM for symptom-disease relationships.

Symptoms	Heart Attack (Disease 1) T	Heart Attack (Disease 1) I	Heart Attack (Disease 1) F	Chronic Fatigue Syndrome (Disease 2) T	Chronic Fatigue Syndrome (Disease 2) I	Chronic Fatigue Syndrome (Disease 2) F
Chest Pain (Symptom 1)	0.7	0.2	0.1	0.2	0.5	0.3
Fatigue (Symptom 2)	0.4	0.3	0.3	0.7	0.2	0.1
Age (55 years old)	0.8	0.1	0.1	0.3	0.4	0.3
High Cholesterol (MH)	0.6	0.2	0.2	0.2	0.5	0.3

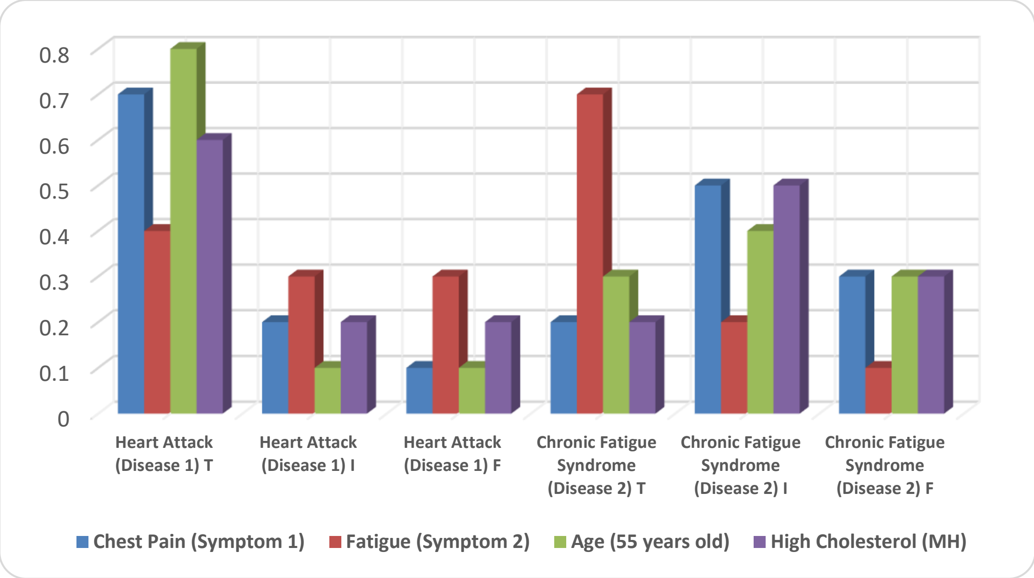

Figure 3. Neutrosophic associations of symptoms, patient data, and potential diagnoses.

Explanation of Values (Considering Patient Data):

- Chest Pain (Symptom 1) & Heart Attack (Disease 1): (Considering Age and Medical History).
    - Truth (T) is increased to 0.8 due to the patient's age (55 years old) being a risk factor for heart attack.
    - Indeterminacy (I) remains moderate (0.2) as other causes of chest pain cannot be ruled out entirely.
- Fatigue (Symptom 2) & Heart Attack (Disease 1): (Considering Age and Medical History)
    - Truth (T) is decreased to 0.4 because fatigue, while a possible symptom, is not the most prominent indicator of heart attack in this case.
- Chest Pain (Symptom 1) & Chronic Fatigue Syndrome (Disease 2): (Considering Age)
    - Truth (T) is decreased to 0.2 as chest pain is less common in Chronic Fatigue Syndrome.
    - Indeterminacy (I) is increased to 0.5 due to the possibility of this symptom being related to the patient's age or other unidentified factors.
- High Cholesterol (Medical History) & Heart Attack (Disease 1):
    - Truth (T) = 0.6 reflects the increased risk of heart attack due to high cholesterol.
- High Cholesterol (Medical History) & Chronic Fatigue Syndrome (Disease 2):
    - Truth (T) = 0.2 (low) as high cholesterol is not directly associated with Chronic Fatigue Syndrome.

This NBRM demonstrates the power of incorporating patient data. The increased Truth (T) value for chest pain and heart attack due to the patient's age highlights the importance of age as a risk factor. Similarly, the decreased Truth (T) value for fatigue and heart attack, along with the high Indeterminacy (I) for chest pain and Chronic Fatigue Syndrome, emphasizes the need for further investigation. This nuanced representation allows healthcare professionals to weigh the influence of various factors and prioritize potential diagnoses based on the specific patient profile.

Application 2: NBRM Operations in Medical Diagnosis

We have two NBRMs representing the relationships between symptoms (Fever, Cough) and potential diseases (Flu, Pneumonia) for two different patients (Patient A and Patient B).

Patient A: This young patient presents with a fever but no cough.

Patient B: This elderly patient presents with both a fever and a cough.

NBRM for Patient A:

Table 5-1. NBRM operations in medical diagnosis.

symptoms	Flu (Disease 1)	Pneumonia (Disease 2)
Fever	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)
Cough	(0, 1, 0)	(0, 1, 0)

Table 5-2. NBRM for Patient A.

Symptoms	Flu (Disease 1) T	Flu (Disease 1) I	Flu (Disease 1)F	Pneumonia (Disease 2) T	Pneumonia (Disease 2) I	Pneumonia (Disease 2) F
Fever	0.8	0.1	0.1	0.5	0.3	0.2
Cough	0.0	1.0	0.0	0.0	1.0	0.0

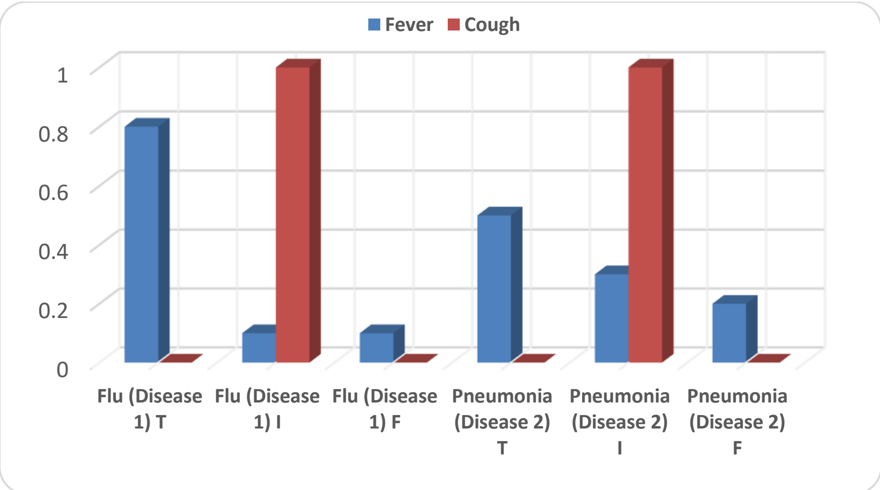

Figure 4. NBRM operations in medical diagnosis.

Explanation:

- Fever:
    - A high Truth (T) for Flu (0.8) indicates a strong association with this disease.
    - Moderate Truth (T) for Pneumonia (0.5) suggests it could be a possibility but less likely than Flu.
    - Both diseases have low Indeterminacy (I) and Falsity (F) values (0.1 and 0.0), suggesting high confidence in these associations.
- Cough:
    - Both Flu and Pneumonia have Truth (T), Indeterminacy (I), and Falsity (F) values of 0.0. This might represent a limitation in the data, as cough is often a symptom of both illnesses.

Further analysis or additional symptoms might be needed for a more definitive conclusion about the association with each disease.

NBRM for Patient B:

Table 6-1. Neutrosophic symptom ratings for diseases.

Symptoms B	Flu (Disease 1)	Pneumonia (Disease 2)
Fever	(0.7, 0.2, 0.1)	(0.4, 0.4, 0.2)
Cough	(0.6, 0.3, 0.1)	(0.5, 0.3, 0.2)

Table 6-2. NBRM for symptoms and diseases.

Symptoms B	Flu (Disease 1) T	Flu (Disease 1) I	Flu (Disease 1) F	Pneumonia (Disease 2) T	Pneumonia (Disease 2) I	Pneumonia (Disease 2) F
Fever	0.7	0.2	0.1	0.4	0.4	0.2
Cough	0.6	0.3	0.1	0.5	0.3	0.2

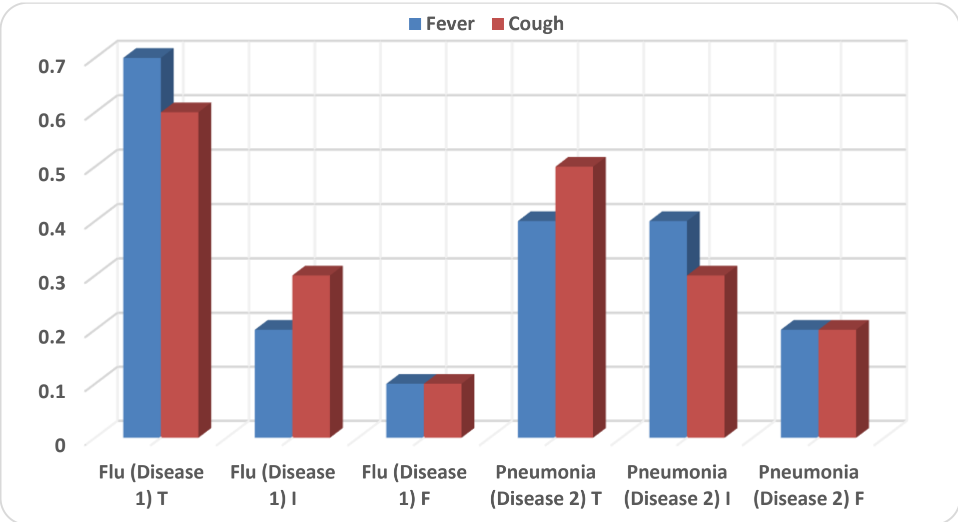

Figure 5. Neutrosophic ratings of symptoms for disease diagnosis.

Let us see how NBRM operations can be used to gain insights:

1. Intersection (Identifying Commonalities):

We can perform an intersection operation on these NBRMs to identify commonalities in the relationships between symptoms and diseases for both patients. Here is the resulting NBRM:

Table 7-1. Intersection of NBRMs for Flu and Pneumonia.

Intersection	Flu (Disease 1)	Pneumonia (Disease 2)
Fever	(0.7, 0.2, 0.1)	(0.4, 0.4, 0.2)

Table 7-2. Neutrosophic Binary Relation Matrix.

Symptoms	Flu (Disease 1) T	Flu (Disease 1) I	Flu (Disease 1) F	Pneumonia (Disease 2) T	Pneumonia (Disease 2) I	Pneumonia (Disease 2) F
Fever	0.7	0.2	0.1	0.4	0.4	0.2

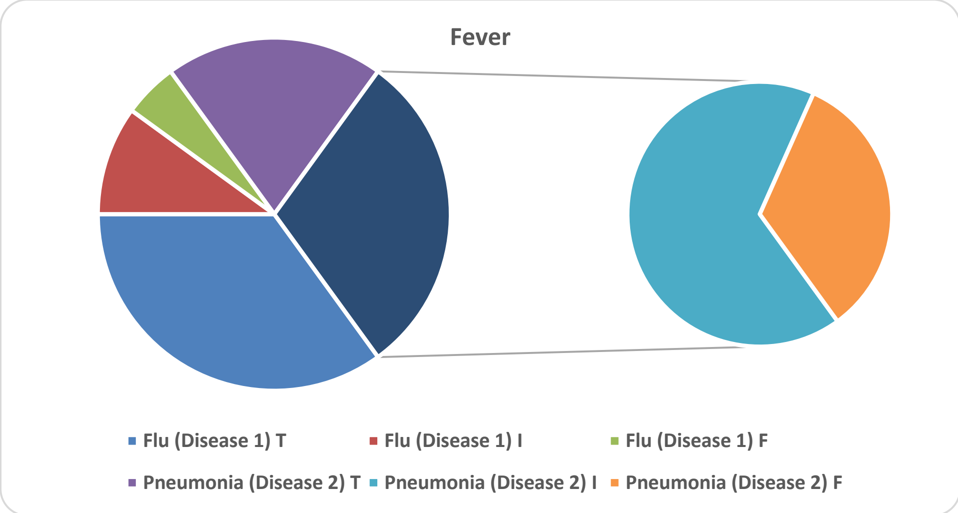

Figure 6. Intersection of NBRMs for Flu and Pneumonia symptoms.

This shows that even though Patient A did not have a cough, both patients share a similar likelihood (T = 0.7) of fever being associated with Flu, with a moderate degree of uncertainty (I = 0.2) about this association. Similarly, for Pneumonia, both patients have a moderate likelihood (T = 0.4) of fever being associated, with a high degree of uncertainty (I = 0.4) due to the possibility of other causes.

2. Union (Broadest Range of Possibilities):

Performing a union operation combines the broadest range of possibilities from both NBRMs:

Table 8. Union of NBRMs for disease diagnosis.

Union	Flu (Disease 1)	Pneumonia (Disease 2)
Fever	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)

Interpretation 1: Highest NBRM Values

If "Union" refers to considering the most prominent association for each disease, the table could represent the following:

Neutrosophic Symptom-Disease Relationships

Symptoms	Flu (Disease 1) T	Flu (Disease 1) I	Flu (Disease 1) F	Pneumonia (Disease 2) T	Pneumonia (Disease 2) I	Pneumonia (Disease 2) F
Fever	0.8 (Highest for Flu)	0.1	0.1	0.5 (Highest for Pneumonia)	0.3	0.2

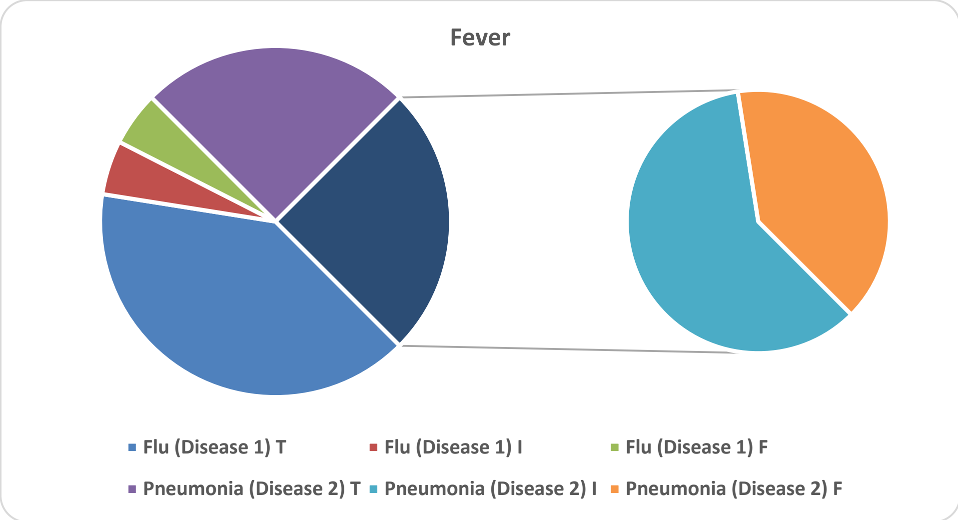

Figure 7. Visualizing the combined evidence: the union of neutrosophic binary relation matrices for disease diagnosis.

This interpretation assumes the "Union" highlights the strongest association (highest T value) for each disease. Here, "Fever" shows a stronger association with Flu (T=0.8) compared to Pneumonia (T=0.5).

Interpretation 2: Combining T Values

Another possible interpretation is that "Union" represents a combined Truth (T) value for each disease, considering all available information (Fever in this case).

This NBRM highlights the highest likelihood (T = 0.8) of fever being associated with Flu for Patient A (based on their NBRM) and captures the possibility of cough (T = 0.6) being associated with Flu for Patient B. Similarly, it reflects the potential association of fever (T = 0.5) and cough (T = 0.5) with Pneumonia for both patients.

3. Complement (Exploring Alternative Diagnoses):

Taking the complement of Patient A's NBRM inverts the T, I, and F values:

Table 9. Complement of patient A's NBRM (exploring alternative diagnoses).

Complement	Flu (Disease 1)	Pneumonia (Disease 2)
Fever	(0.2, 0.9, 0.9)	(0.5, 0.7, 0.8)
Cough	(1, 0, 0)	(1, 0, 0)

NBRM Analysis Table 10:

Table 10-1. NBRM analysis.

Symptoms	Flu (Disease 1)	Pneumonia (Disease 2)
Fever (38.5°C)	T: 0.2, I: 0.9, F: 0.9	T: 0.5, I: 0.7, F: 0.8
Cough	T: 1.0, I: 0.0, F: 0.0	T: 1.0, I: 0.0, F: 0.0

Table 10-2. NBRM analysis Table with separated degrees.

Symptoms	Flu (Disease 1) T	Flu (Disease 1) I	Flu (Disease 1) F	Pneumonia (Disease 2) T	Pneumonia (Disease 2) I	Pneumonia (Disease 2) F
Fever (38.5°C)	0.2	0.9	0.9	0.5	0.7	0.8
Cough	1.0	0.0	0.0	1.0	0.0	0.0

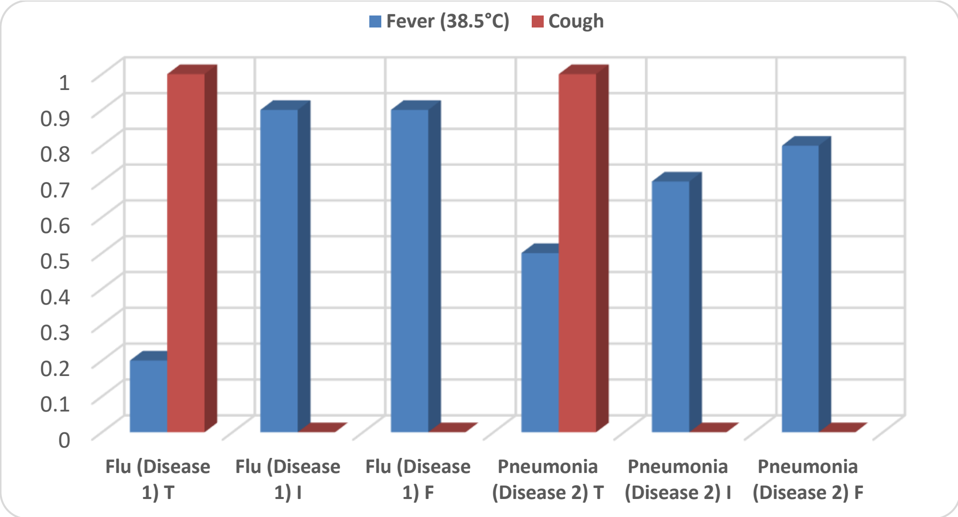

Figure 8. NBRM analysis of symptom-disease relationships with truth (t), indeterminacy (i), and falsity (f) degrees.

While unlikely (due to high F values), this helps explore alternative diagnoses where fever might not be associated with Flu or Pneumonia for Patient A. However, the high I values still indicate some uncertainty in these alternative possibilities.

Interpretation:

By performing these operations on NBRMs, healthcare professionals can gain valuable insights:

- Intersection helps identify common trends across patient presentations.
- Union provides a broader view of all potential associations based on available data.
- Complement allows exploring alternative diagnoses, considering less likely scenarios.

This comprehensive understanding of the relationship between symptoms, diseases, and patient-specific factors can lead to more informed diagnostic decisions and improved patient care.

4 | Applications in Medical Diagnosis

NBRMs hold immense potential for enhancing medical diagnosis by offering a way to model complex relationships with varying degrees of certainty and uncertainty. Here is how they can be applied:

4.1 | Modeling Complex Relationships

Symptom-Disease Relationships with Uncertainty: Traditional methods often assign a binary (present/absent) value to symptoms. NBRMs can represent the degree to which a symptom is typically associated with a disease (T), the degree of uncertainty due to potential variations or atypical presentations (I), and the possibility that the symptom is unrelated (F). This allows for a more accurate reflection of real-world scenarios.

For Application, a fever might have a high T value for associating with an infection but also have a moderate I value due to potential causes like medication side effects.

Application: NBRM for Fever and Potential Causes

Scenario: A patient presents with a fever (38.5°C). We want to represent the association of this fever with two potential causes: Infection (Disease 1) and Medication Side Effects (Disease 2) using an NBRM.

Sets:

Row Set (Symptom): {Fever (38.5°C)}.

Column Set (Diseases): {Infection (Disease 1), Medication Side Effect (Disease 2)}.

Neutrosophic Binary Relation Matrix:

Table 11-1. NBRM for fever and potential causes.

Symptom	Infection (Disease 1)	Medication Side Effect (Disease 2)
Fever (38.5°C)	(0.8, 0.1, 0.1)	(0.5, 0.3, 0.2)

Table 11-2. NBRM for symptom-disease relationships.

Symptoms	Symptom Description	Infection (Disease 1) T	Infection (Disease 1) I	Infection (Disease 1) F	Medication Side Effect (Disease 2) T	Medication Side Effect (Disease 2) I	Medication Side Effect (Disease 2) F
Fever	38.5°C	0.8	0.1	0.1	0.5	0.3	0.2

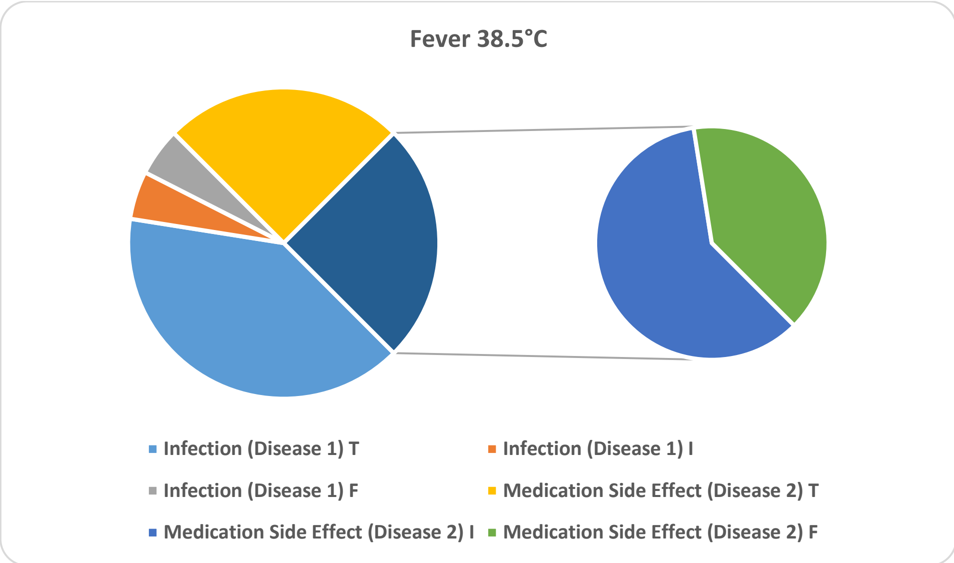

Figure 9. NBRM: fever vs. potential causes (truth, indeterminacy, falsity).

Explanation:

Symptom Description: This column clarifies the specific characteristic of the symptom (Fever temperature in this case).

Infection (Disease 1) T, I, F: These columns represent the Truth (likelihood), Indeterminacy (uncertainty), and Falsity (no association) values for the association between fever (at 38.5°C) and Infection.

Medication Side Effect (Disease 2) T, I, F: These columns represent the corresponding NBRM values for the association between fever (at 38.5°C) and Medication Side Effects.

This format provides a clearer understanding of how a specific symptom value (Fever at 38.5°C) relates to each potential disease.

Explanation of Values:

Fever (38.5°C) & Infection (Disease 1):

Truth (T) = 0.8: There is a high likelihood (0.8) that a fever of this degree is associated with an infection.

Indeterminacy (I) = 0.1: There is a low degree of uncertainty (0.1) about this association. This could be due to other factors causing a slightly elevated temperature.

Falsity (F) = 0.1: There is a low possibility (0.1) that this fever is unrelated to an infection.

Fever (38.5°C) & Medication Side Effect (Disease 2):

Truth (T) = 0.5: There is a moderate likelihood (0.5) that a fever of this degree could be a side effect of medication.

Indeterminacy (I) = 0.3: There is a moderate degree of uncertainty (0.3) about this association. This could be due to several factors:

The specific medication the patient is taking and its known side effects.

The absence of information about recent medication changes.

Falsity (F) = 0.2: There is a low-to-moderate possibility (0.2) that this fever is unrelated to a medication side effect.

Interpretation:

This NBRM highlights the advantage of representing uncertainty compared to a binary approach. While fever is highly suggestive of an infection, the I value acknowledges the possibility of medication side effects. This prompts further investigation into the patient's medication history, potentially leading to a faster and more accurate diagnosis.

Patient Data Analysis: NBRMs can be expanded to include additional rows or columns for incorporating patient-specific data like age, allergies, and medical history. The T, I, and F values in these entries can reflect how these factors influence the overall relationship between symptoms and diseases for a particular patient.

Consider a patient with a history of autoimmune disease. An NBRM might assign a higher I value to the association between a fever and a typical infection due to the possibility of an autoimmune flare-up.

Application 3: NBRM with Patient Data Integration

A 42-year-old female patient with a history of autoimmune disease presents with a fever (38.7°C). We want to represent the association of this fever with two potential causes: Infection (Disease 1) and Autoimmune Flare-Up (Disease 2) using an NBRM, considering the patient's medical history.

Sets:

Row Set (Symptom & Patient Data): {Fever (38.7°C), Autoimmune Disease History}.

Column Set (Diseases): {Infection (Disease 1), Autoimmune Flare-Up (Disease 2)}.

Neutrosophic Binary Relation Matrix:

Table 12-1. NBRM for fever and potential causes in a patient with autoimmune disease history.

	Infection (Disease 1)	**Autoimmune Flare-Up (Disease 2)**
Fever (38.7°C)	(0.8, 0.1, 0.1)	(0.6, 0.3, 0.1)

Table 12-2. Neutrosophic Binary Relation Matrix.

Symptoms	**Flu (Disease 1) (Change to Infection)**	**T (Tru th)**	**I (Indeterminacy)**	**F (Falsity)**	**Autoimmune Flare-Up (Disease 2)**	**T (Truth)**	**I (Indeterminacy)**	**F (Falsity)**
Fever (38.7°C)	Infection (Disease 1)	0.8	0.1	0.1	Autoimmune Flare-Up (Disease 2)	0.6	0.3	0.1

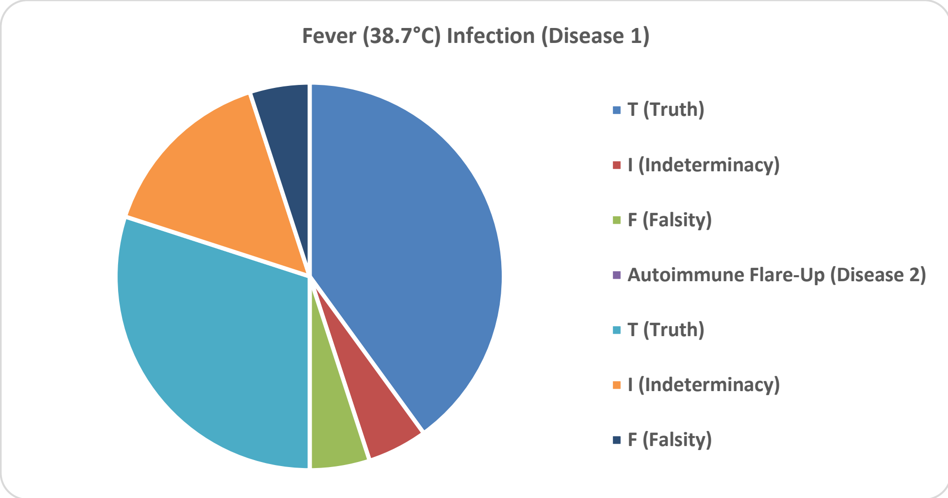

Figure 10. Neutrosophic relationships between fever and potential causes in an autoimmune patient.

Explanation of Values:

Fever (38.7°C) & Infection (Disease 1): (Considering Patient Data)

Truth (T) = 0.8: There is still a high likelihood (0.8) that a fever of this degree is associated with an infection.

Indeterminacy (I) is increased to 0.1 due to the patient's history of autoimmune disease, introducing some uncertainty about the cause of the fever.

Autoimmune Disease History: (Certainty for Disease 2)

This row is included to represent the patient's medical history as a factor influencing the overall analysis.

Since this row relates to the existence of a disease (Autoimmune Disease), all values are set to 1 (Truth), 0 (Indeterminacy), and 0 (Falsity) to indicate absolute certainty about the patient's medical history.

Fever (38.7°C) & Autoimmune Flare-Up (Disease 2): (Considering Patient Data)

Truth (T) = 0.6: The patient's history increases the likelihood (0.6) that the fever could be due to an autoimmune flare-up.

Indeterminacy (I) = 0.3: There is still a moderate degree of uncertainty (0.3) as other factors like infection cannot be entirely ruled out.

This NBRM demonstrates how incorporating patient data can refine the analysis. While fever remains suggestive of infection, the increased I value indicates the need for further investigation due to the patient's specific medical history. This allows for a more nuanced understanding of the potential causes and a more informed approach to diagnosis.

Explanation of Values in a Doctor Decision Support System using NBRMs

This explanation focuses on the concept of using NBRMs (Neurally Based Relational Models) in doctor decision support systems, using the Application of fever and potential diagnoses.

A patient presents with a fever of 38.7°C. The doctor utilizes a decision support system that incorporates NBRMs to analyze potential causes, considering the patient's medical history of autoimmune disease.

Data:

Symptom: Fever (38.7°C)

Patient Data: History of Autoimmune Disease

Potential Diagnoses:

Infection (Disease 1)

Autoimmune Flare-Up (Disease 2)

NBRM Analysis Breakdown:

Fever (38.7°C) & Infection (Disease 1):

Truth (T) = 0.8: This value indicates a high likelihood (0.8) that a fever of this degree is associated with an infection in general.

Indeterminacy (I) = 0.1: The indeterminacy is slightly increased to 0.1 due to the patient's history of autoimmune disease. This introduces some uncertainty about the specific cause of the fever in this particular case.

Autoimmune Disease History (Certainty for Disease 2):

Truth (T) = 1: Since this row represents a confirmed medical history (autoimmune disease), the Truth value is set to 1, indicating absolute certainty about the patient's existing condition.

Indeterminacy (I) = 0: As the patient has a diagnosed autoimmune disease, there's no indeterminacy about its existence (I = 0).

Falsity (F) = 0: Similarly, the Falsity value is 0 because the patient's medical history is confirmed.

Fever (38.7°C) & Autoimmune Flare-Up (Disease 2):

Truth (T) = 0.6: The patient's history of autoimmune disease increases the likelihood (0.6) that the fever could be due to an autoimmune flare-up.

Indeterminacy (I) = 0.3: There is still a moderate degree of uncertainty (0.3) because other factors like those that infection cannot be entirely ruled out based solely on the fever.

This NBRM analysis demonstrates the value of incorporating patient data into the decision-making process. While a fever of 38.7°C generally suggests a high likelihood of infection (T = 0.8 for Disease 1), the patient's autoimmune history introduces some uncertainty (increased I value). This highlights the need for further investigation beyond just the fever itself.

Benefits of NBRMs in Decision Support Systems:

Nuanced View: NBRMs provide a more comprehensive picture by considering both general symptom-disease associations (high T for fever infection) and patient-specific factors (increased I due to autoimmune history).

Improved Decision-Making: Doctors can weigh different possibilities based on Truth and Indeterminacy values, leading to more informed diagnostic approaches.

Reduced Uncertainty: NBRMs highlight areas of uncertainty, prompting further investigation or tests to refine the diagnosis.

Overall, NBRMs in doctor decision support systems can enhance patient care by providing a more nuanced view of potential causes and guiding a more informed diagnostic and treatment approach.

Decision Support Systems for Doctors: NBRMs can be integrated into decision support systems for doctors. By analyzing patient data and symptom presentations represented as NBRMs, these systems can provide a more nuanced view of potential diagnoses. They can:

Consider multiple possibilities simultaneously, taking into account the T, I, and F values for various symptom-disease associations.

Highlight potential interactions between medications and symptoms, represented by F values increasing in the NBRM when specific medications are present.

Recommend further tests based on the degree of indeterminacy (I) associated with certain diagnoses, helping to refine the decision-making process.

This provides doctors with a more comprehensive picture and facilitates the selection of the most appropriate diagnostic course for each patient.

Decision Support System Insights:

Multiple Possibilities:

The NBRM highlights both Heart Disease and Anxiety Attack as possibilities.

High T values for chest pain and age point towards Heart Disease.

Moderate T for fatigue suggests both Heart Disease and Anxiety Attack.

Medication Interaction:

The doctor can analyze further if any medications for hypertension might be causing fatigue (increasing F value in the NBRM).

Indeterminacy and Further Tests:

Moderate I values for fatigue and chest pain indicate some uncertainty.

The system could recommend additional tests (EKG, blood pressure monitoring) based on the high I values associated with Heart Disease.

Doctor's Decision:

Based on the NBRM analysis, the doctor can:

Prioritize investigating Heart Disease due to the high T values and risk factors.

Consider Anxiety Attack as a possibility based on fatigue and moderate I values.

Order further tests to reduce I and confirm/rule out diagnoses.

Benefits:

Nuanced View: Provides a more nuanced picture compared to binary approaches.

Improved Decision Making: Helps doctors consider all possibilities and prioritize investigations.

Reduced Uncertainty: Recommends tests based on indeterminacy to refine the diagnosis.

This Application demonstrates how NBRMs can enhance doctor decision support systems, leading to more accurate diagnoses and better patient care.

4.2 | Specific Medical Applications

Disease Prediction: NBRMs can be used to analyze historical data and identify patterns in symptom presentation and disease progression. This can help predict the likelihood of developing specific diseases based on an individual's current symptoms and medical history, represented by NBRMs.

For Application, NBRMs can be used to analyze long-term patient data and identify early warning signs for chronic conditions like diabetes or heart disease.

Personalized Medicine: NBRMs can be valuable tools for personalized medicine by tailoring treatment plans to individual patient profiles. By incorporating patient-specific data and its influence on symptom-disease relationships, NBRMs can help identify the most effective treatment options for each patient.

Consider a patient with a specific genetic mutation known to influence response to certain medications. NBRMs can be used to adjust the F value in the NBRM for specific drug-disease associations, guiding doctors toward the most appropriate therapy.

In conclusion, NBRMs offer a promising avenue for enhancing medical diagnosis by providing a framework for modeling complex relationships with inherent uncertainty. By incorporating patient-specific data and allowing for a more nuanced understanding of symptom-disease associations, NBRMs have the potential to revolutionize healthcare by enabling disease prediction, personalized medicine, and ultimately, improved patient outcomes.

Application 4: NBRM for Disease Prediction (Diabetes)

We want to analyze historical data from a group of patients to identify potential early warning signs for developing Type 2 Diabetes (Disease). We will use NBRMs to represent the association between various risk factors (symptoms) and the development of diabetes.

Data:

Risk Factors (Symptoms): Increased thirst (I.Thirst), Frequent urination (F.Urination), Fatigue (Fatigue).

Patient Data: Age (over 40), Family history of diabetes (F.History).

NBRM Analysis:

Table 13-1. NBRM for disease prediction (diabetes).

	Type 2 Diabetes (Disease)
I.Thirst	(0.7, 0.2, 0.1)
F.Urination	(0.8, 0.1, 0.1)
Fatigue	(0.5, 0.3, 0.2)
Age (>40)	(0.6, 0.2, 0.2)
F.History	(0.8, 0.1, 0.1)

Table 13-2. Symptom-data relationships using neutrosophic logic.

Symptom/Data	**Truth (T)**	**Indeterminacy (I)**	**Falsity (F)**
Thirst	0.7	0.2	0.1
Urination	0.8	0.1	0.1
Fatigue	0.5	0.3	0.2
Age (>40)	0.6	0.2	0.2
Family History	0.8	0.1	0.1

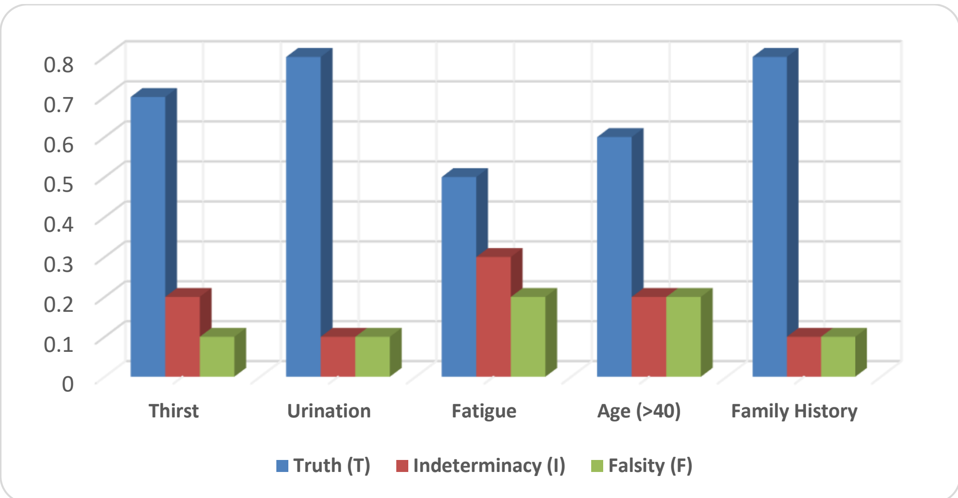

Figure 11. Distribution of truth, indeterminacy, and falsity in nbrm for diabetes prediction.

Interpretation:

The NBRM highlights increased thirst and frequent urination as strong potential early warning signs for diabetes (high T values).

While fatigue is a possible symptom, the moderate T value indicates it might not be as specific for early diabetes prediction in this analysis.

Age over 40 and a family history further increase the likelihood of developing diabetes (high T values).

Benefits:

This analysis helps identify potential early warning signs for diabetes based on historical data.

Doctors can use this information to encourage preventative measures or earlier testing for at-risk patients with similar NBRM profiles.

Limitations and Future Considerations:

This is a simplified Application. Real-world data might have more complex relationships and require additional factors.

Further research is needed to validate the effectiveness of NBRM-based prediction models in clinical settings.

Application 5: NBRM for Personalized Medicine (Cancer Treatment)

A patient diagnosed with a specific type of breast cancer undergoes genetic testing, revealing a mutation known to affect their response to certain chemotherapy drugs (Drug A and Drug B). We can use an NBRM to represent the effectiveness of these drugs for this specific patient.

Data:

Drugs: Drug A, Drug B

Patient Data: Genetic Mutation (M1)

NBRM Analysis:

Table 14. NBRM for personalized medicine (cancer treatment).

	Effectiveness (Disease Free)
Drug A	(0.7, 0.2, 0.1)
Drug B	(0.4, 0.4, 0.2)

Drug	**Truth (T)**	**Indeterminacy (I)**	**Falsity (F)**
Drug A	0.7	0.2	0.1
Drug B	0.4	0.4	0.2

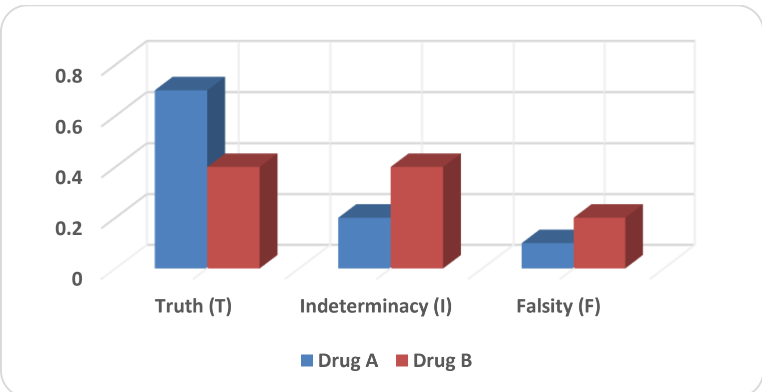

Figure 12. Truth, indeterminacy, and falsity of drug effectiveness (disease free) in breast cancer treatment (m1 mutation).

Explanation:

Drug A has a high Truth (T) value (0.7) indicating a good chance of achieving disease-free status.

The patient's genetic mutation (M1) influences the NBRM for Drug B. The Truth (T) value is reduced to 0.4, reflecting the lower effectiveness of this drug due to the mutation. The Indeterminacy (I) value is increased (0.4) to acknowledge some uncertainty in the response even with the mutation.

Benefits:

This NBRM helps personalize the treatment plan by identifying Drug A as a potentially more effective option for this specific patient.

By adjusting the NBRM based on genetic data, doctors can make informed decisions about the most suitable therapy.

Limitations and Future Considerations:

This is a simplified Application. Real-world treatment decisions involve multiple factors and potential side effects.

NBRMs need further development to integrate with comprehensive patient data and treatment options for personalized medicine.

These Applications highlight the potential of NBRMs in disease prediction and personalized medicine. While limitations exist, ongoing research paves the way for NBRMs to revolutionize healthcare by providing a more nuanced and data-driven approach to diagnosis and treatment.

Application 6: Neutrosophic Binary Relation Matrix (NBRM) Example for Enhanced Medical Diagnosis

This example displays an NBRM representing the relationship between five symptoms (S1 - S5) and three potential diseases (D1 - D3). The values represent the degree of Truth (T), Indeterminacy (I), and Falsity (F) associated with each symptom-disease pairing.

	Disease 1 (D1)	**Disease 2 (D2)**	**Disease 3 (D3)**
Symptom 1 (S1)	(0.7, 0.2, 0.1)	(0.3, 0.4, 0.3)	(0.2, 0.5, 0.3)
Symptom 2 (S2)	(0.4, 0.3, 0.3)	(0.8, 0.1, 0.1)	(0.1, 0.6, 0.3)
Symptom 3 (S3)	(0.2, 0.5, 0.3)	(0.1, 0.7, 0.2)	(0.7, 0.2, 0.1)
Symptom 4 (S4)	(0.1, 0.6, 0.3)	(0.2, 0.5, 0.3)	(0.8, 0.1, 0.1)
Symptom 5 (S5)	(0.5, 0.3, 0.2)	(0.4, 0.4, 0.2)	(0.3, 0.4, 0.3)

Interpretation:

- S1 (Fever):
    - D1 (High chance): There is a high Truth (0.7) value indicating fever is strongly suggestive of Disease 1.
    - D2 (Moderate chance): A moderate Truth (0.3) suggests fever has some association with Disease 2 but with more indeterminacy (0.4).
    - D3 (Low chance): The low Truth (0.2) and high Falsity (0.3) indicate fever is unlikely to be a strong indicator of Disease 3.
- S2 (Cough):
    - D2 (High chance): Similar to S1, D2 has a high Truth (0.8) value, suggesting a strong link between cough and Disease 2.

- D1 (Moderate chance): There's a moderate Truth (0.4) for Disease 1, but also significant indeterminacy (0.3).
- D3 (Low chance): Similar to S1 and Disease 3, the low Truth and high Falsity suggest a weak connection.

- S3 (Rash):
  - D3 (High chance): This entry shows a strong association between rash and Disease 3 (Truth: 0.7).
  - D1 & D2 (Moderate chances): Both D1 (0.2) and D2 (0.1) have lower Truth values for rash, indicating a weaker connection with more indeterminacy (0.5 & 0.7) compared to D3.
- S4 (Headache):
  - D3 (High chance): Similar to S3, headache has a high Truth (0.8) for Disease 3.
  - D1 & D2 (Low chances): Both D1 (0.1) and D2 (0.2) have low Truth values and high Falsity for headache, suggesting a weak link.
- S5 (Fatigue):
  - All Diseases (Moderate chances): This symptom has moderate Truth values (around 0.5) for all three diseases, indicating some level of association but also significant indeterminacy (around 0.3) in each case.
- Benefits of NBRMs in Medical Diagnosis:
  - Accounting for Uncertainty: NBRMs capture the "in-between" states by incorporating Truth, Indeterminacy, and Falsity degrees, providing a more nuanced picture than traditional binary relationships.
  - Improved Decision Making: By considering these different degrees, healthcare professionals can make more informed diagnoses by weighing the evidence alongside the inherent uncertainties.
  - Incorporating Incomplete Information: NBRMs can handle missing data by assigning appropriate indeterminacy values, leading to diagnoses that are more robust even with incomplete information.

5 | Advantages and Limitations

NBRMs present a compelling approach to medical diagnosis by offering a way to handle the inherent uncertainties and complexities of real-world clinical scenarios. However, like any new technology, they come with both advantages and limitations that need careful consideration.

5.1 | Advantages of NBRMs

- Embracing Uncertainty: Traditional methods often struggle with the ambiguity surrounding symptoms and disease associations. NBRMs, with their T (Truth), I (Indeterminacy), and F (Falsity) degrees, can represent the likelihood, uncertainty, and unlikelihood of a relationship. This nuanced approach provides a more accurate reflection of real-world situations where symptoms might be suggestive (T) but not definitive (high I) of a specific disease.
- Richer Representation of Relationships: Medical diagnosis involves intricate relationships between symptoms, diseases, and patient factors. NBRMs allow for the modeling of these intricate relationships by incorporating patient data and its influence on symptom-disease associations. This

leads to a more comprehensive understanding of a patient's unique condition, considering individual complexities.

- Enhanced Decision-Making and Diagnosis: By considering multiple possibilities through the T, I, and F values, and providing a more nuanced view of potential diagnoses, NBRMs can assist healthcare professionals in making more decisions that are informed. This can lead to a higher degree of diagnostic accuracy, potentially resulting in faster and more effective treatment plans.

5.2 | Limitations of NBRMs

- Computational Challenges: Performing operations on NBRMs, such as intersection, union, and complement, can be computationally intensive. This can pose a challenge for real-time applications in busy clinical settings. Efficient algorithms and robust computing infrastructure are necessary for practical implementation.
- Data Dependence: NBRMs are highly reliant on the quality and completeness of medical data. Inaccurate or incomplete data can lead to unreliable results and potentially erroneous diagnoses. Robust data collection methods, data cleaning procedures, and data standardization are crucial for NBRMs to be effective.
- Early Stage of Development: While NBRMs hold significant promise, they are still under development. Further research is necessary in several areas:
  - Developing efficient algorithms for NBRM operations to ensure faster processing and real-time applications.
  - Standardizing data formats to allow seamless integration of NBRMs with existing electronic health records (EHR) systems.
  - Conducting clinical trials to validate the effectiveness of NBRMs in improving diagnostic accuracy and patient outcomes.

These limitations require ongoing research and development to ensure NBRMs can be effectively integrated into clinical practice.

In conclusion, NBRMs offer a powerful tool for managing uncertainty in medical diagnosis. Their ability to represent complex relationships more accurately holds immense potential for improved decision-making and diagnosis accuracy. However, addressing the limitations through focused research and development efforts is crucial for realizing the full potential of NBRMs in revolutionizing healthcare.

6 | Conclusion

NBRMs emerge as a promising tool for enhancing medical diagnosis by offering a way to handle the inherent uncertainties and complexities present in real-world scenarios. Their ability to represent relationships between symptoms, diseases, and patient factors using truth (T), indeterminacy (I), and falsity (F) degrees provides a richer framework compared to traditional binary methods. NBRMs hold significant potential for:

- Improved Accuracy: By capturing the "in-between" states often encountered in medical data, NBRMs can lead to a more accurate reflection of a patient's condition, potentially reducing misdiagnosis and delayed diagnosis.
- Enhanced Decision-Making: By considering multiple possibilities and providing a nuanced view of potential diagnoses, NBRMs can assist healthcare professionals in making more informed decisions, leading to better treatment plans.

- Personalized Medicine: NBRMs can be instrumental in personalized medicine by incorporating patient-specific data and its influence on symptom-disease associations, allowing for tailored treatment approaches.

However, it is crucial to acknowledge that NBRMs are still under development. Further research is necessary to:

- Address Computational Complexity: Develop efficient algorithms for NBRM operations to ensure real-time applicability in clinical settings.
- Improve Data Quality: Implement robust data collection methods and data cleaning procedures to guarantee the reliability of NBRM results.
- Validate Effectiveness: Conduct clinical trials to validate the effectiveness of NBRMs in improving diagnostic accuracy and patient outcomes.

Despite these limitations, the potential benefits of NBRMs are undeniable. Continued research and development efforts hold the key to unlocking the full potential of NBRMs in revolutionizing medical diagnosis and ultimately, improving patient care.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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