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Neutrosophy, Causal AI, and Web3: combo for complex decision-making

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Abstract: This article introduces Neutrosophic Causal AI, a novel framework that integrates neutrosophic logic with structural causal models to enhance decision-making under uncertainty. While traditional Causal AI is effective at identifying cause-and-effect relationships, it assumes a level of precision rarely found in complex, real-world systems. By incorporating degrees of truth (T), indeterminacy (I), and falsity (F), Neutrosophic Causal AI extends causal inference to accommodate ambiguity, contradiction, and incomplete data. The proposed framework formalizes the neutrosophic do-operator and adapts Judea Pearl's structural causal models to a neutrosophic context, allowing for more nuanced intervention analysis and counterfactual reasoning. Through illustrative examples and a simulation-based approach, the article demonstrates how this method improves transparency and epistemic robustness in decision systems. Special attention is given to applications in Web3 environments, where decentralized governance, smart contracts, and autonomous decision-making require high levels of reliability and trust. Neutrosophic Causal AI thus emerges as a critical tool for building intelligent systems that reflect the complexity of social and digital ecosystems, providing a bridge between computational logic, causal analysis, and real-world ambiguity.

Keywords: Neutrosophic Causal AI; do-operator; uncertainty modeling; causal inference; Web3 applications.

1. Introduction

Addressing complex decisions amidst vague and uncertain data necessitates innovative approaches. This paper explores the integration of Neutrosophy[1], Causal AI [2], and Web3 [3] technologies. Combining Neutrosophy and Causal AI we have Neutrosophic Causal AI, a powerful framework to support decision-making.

Traditional AI, and advanced machine learning methods, such as large language models (LLMs), rely primarily on statistical correlations, learning from extensive datasets to make predictions but exhibiting a limited ability to identify causal relationships from data [4]. Causal AI, conversely, developed methods to identify cause-and-effect relationships from either observational or experimental data [5].

Web3 [6,7,8], with its decentralized nature and smart contract automation, demands robust, verifiable decision-making. By integrating Neutrosophic Causal AI, we can move beyond mere prediction to understand the underlying causal mechanisms, enabling more accurate and reliable outcomes when in contexts where data contain indeterminacy and ambiguity.

Recent research has increasingly sought to bridge causal reasoning with the domain of Neutrosophy. While existing approaches like Neutrosophic Cognitive Maps (NCMs) [9, 10] and Neutrosophic Qualitative Comparative Analysis (NQCA) [11, 12, 13] offer promising frameworks for modeling complex systems rife with indeterminacy and contradiction, they currently lack certain formalisms standard in established causal inference. Notably, these methods have not yet incorporated an equivalent to Pearl's do-calculus[14, 15] for rigorous intervention analysis, nor have they explicitly adopted the mathematical underpinnings of Structural Causal Models (SCMs)[17, 18, 19]. This gap highlights both a limitation of current neutrosophic causal methods in handling formal intervention queries and an opportunity for future work to potentially integrate Pearl's well-founded tools to enhance their analytical capabilities.

This article addresses that gap by approaching the integration of Neutrosophic Logic and Causal AI not just as a conceptual fusion, but as a formal modeling problem. We introduce a new formulation—Neutrosophic Causal AI—which explicitly adapts structural causal models and do-operators to the neutrosophic context, providing tools to simulate interventions and estimate causal effects in environments characterized by vagueness, inconsistency, and uncertainty.

The remainder of this paper is structured as follows. Section 2 provides the theoretical foundations of Causal AI, including structural causal models, DAGs, and the principles of Pearl's do-calculus. Section 3 introduces the concept of Neutrosophic Causal AI, detailing how neutrosophic logic extends traditional causal reasoning frameworks. We also define the neutrosophic do-operator and present illustrative examples of causal effect estimation using neutrosophic probabilities. Section 4 explores practical applications of Neutrosophic Causal AI in Web3 and blockchain environments. Finally, Section 5 summarizes the key contributions and discusses implications for future research in AI, logic, and decentralized systems.

2. Preliminaries

2.1 Causal AI

Causal Artificial Intelligence (Causal AI) represents a paradigm shift in machine learning, moving beyond mere pattern recognition to the understanding of cause-and-effect relationships. As defined by Ness [5], Causal AI involves the automation of causal reasoning through machine learning, enabling systems to not only predict but also explain outcomes [20]. This automation is crucial for navigating the complexity of real-world systems, where understanding the 'why' behind observed phenomena is as important as the 'what.'

Expanding on this, Hurwitz and Thompson [2] characterize Causal AI as both an art and a science, emphasizing the intricate analysis of variable relationships to discern relevant causes and effects within a system. This perspective highlights the comprehensive approach required to effectively manage and understand complex systems.

We define Causal AI as a systematic approach that seeks to understand cause-and-effect relationships from data (experimental or observational) to support decision-making. The systematic approach steps are a) problem contextualization, b) causal modeling with graphs (DAGs), and c) quantitative validation of causal relationships.

A key aspect of Causal AI, as underscored by Ness [5], is its reliance on causal inference, which allows data scientists to simulate experiments and estimate causal effects from observational data. This is particularly significant given that most data, including 'big data,' is observational, not experimental [5]. Causal AI thus empowers researchers to extract meaningful causal insights from naturally occurring data, bridging the gap between passive observation and active experimentation[21].

2.2.1 Causal Structural Model

At the core of Causal AI lies the Causal Structural Model (CSM)[16], often represented by Directed Acyclic Graphs (DAGs)[22]. These graphical models depict causal relationships between variables, where nodes represent variables and directed edges indicate the direction of causality.

The DAG structure captures the conditional dependencies between variables, enabling the representation of causal hypotheses about the system under study[23]. Recognizing structures like 'chain,' 'fork,' and 'collider' within these DAGs is crucial, as they dictate how causal information flows and how interventions should be analyzed.

A 'chain' (A → B → C) represents a direct causal flow, a 'fork' (B ← A → C) indicates a common cause generating multiple effects, and a 'collider' (A → C ← B) signals a point where multiple causes converge on an effect, requiring care to avoid selection biases (Figure 1).

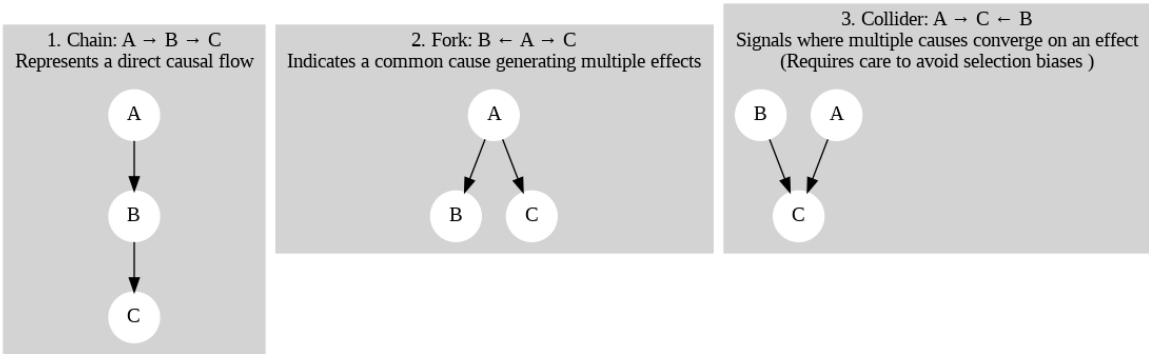

Figure 1. Fundamental Causal Structures.

The diagrams represent the three basic causal topologies: (1) Chain (direct causal flow A→B→C), (2) Fork (common cause B←A→C), and (3) Collider (common effect A→C←B). Correct analysis of these structures is essential for causal inference and the identification of potential biases.

Through CSM, and with an understanding of these structures, it is possible to visualize and analyze cause-and-effect relationships, facilitating the identification of potential confounders and mediators, which are crucial for accurate causal inference.

The 'do-operation,' introduced by Judea Pearl, is an essential tool in this context, allowing for the simulation of interventions by 'cutting' the incoming edges of the intervened variable, enabling the estimation of specific causal effects and the simulation of counterfactual scenarios.

The foundation of causal AI has roots in Pearl's research regarding causal inference. Pearl synthesized the causal inference through the ladder of causation[24].

Definition 1. Definition of the do-Operator in Pearl's Causal Framework[25-28]:

Within the formalism of Structural Causal Models (SCMs) developed by Judea Pearl, a model M consists of a set of variables (endogenous V and exogenous U), and a set of functions F that determine the value of each endogenous variable V_i based on its direct causal parents (〖pa〗_i) in the associated causal graph and the corresponding exogenous variables (u_i). Each structural equation takes the form:

$$V_i = f_i(pa_i, u_i) \quad (1)$$

The $\boldsymbol{do}(\boldsymbol{X} = \boldsymbol{x})$ operator represents an external intervention that fixes the value of a variable (or set of variables) $\boldsymbol{X} \subseteq \boldsymbol{V}$ to a constant $\boldsymbol{x}$. This operation is fundamental for distinguishing between passive observation and deliberate action (or setting), thereby allowing the definition and calculation of causal effects.

Formally, applying the $\boldsymbol{do}(\boldsymbol{X}=\boldsymbol{x})$ operator to a model $\boldsymbol{M}$ generates a new, modified model, denoted $\boldsymbol{M_x}$. This submodel $\boldsymbol{M_x}$ is obtained from $\boldsymbol{M}$ through the following procedure:

The structural equations within $\boldsymbol{F}$ that determine the variables in $\boldsymbol{X}$ are removed.

1 These equations are replaced by assigning the constant value $\boldsymbol{x}$ to the variables $\boldsymbol{X}$.
2 All other structural equations from model M remain unchanged.
3 The probability distribution $\boldsymbol{P}(\boldsymbol{u})$ over the exogenous variables $\boldsymbol{U}$ remains the same as in M.

The probability distribution of a variable (or set of variables) $\boldsymbol{Y} \subseteq \boldsymbol{V}$ under the intervention $\boldsymbol{do}(\boldsymbol{X}=\boldsymbol{x})$ is denoted as $\boldsymbol{P}(\boldsymbol{Y}=\boldsymbol{y} \mid \boldsymbol{do}(\boldsymbol{X}=\boldsymbol{x}))$. This distribution represents the behavior of $\boldsymbol{Y}$ in the hypothetical scenario where $\boldsymbol{X}$ is forced to take the value $\boldsymbol{x}$. It is formally defined as the probability distribution of $\boldsymbol{Y}$ in the modified model $\boldsymbol{M_x}$:

$$P(Y=y \mid do(X=x)) = P_{m_x}(Y=y) \quad (2)$$

Where $\boldsymbol{P_{m_x}}(\boldsymbol{Y}=\boldsymbol{y})$ is the probability that Y takes the value y induced by the submodel $\boldsymbol{M_x}$and the distribution $\boldsymbol{P}(\boldsymbol{u})$. This mathematical construct allows for the rigorous quantification of the causal effects of interventions, distinguishing them from mere statistical associations observed in the data.

Example 1: Calculation of the Causal Effect of a Treatment via Covariate Adjustment

Scenario: Consider an observational study to evaluate the effect of a new Treatment (X) on Recovery (Y) from a disease. It is known that the patient's Age (Z) can influence both the decision to take the treatment and the probability of recovery, thus acting as a confounding factor. We assume the following causal structure, represented by a Directed Acyclic Graph (DAG):

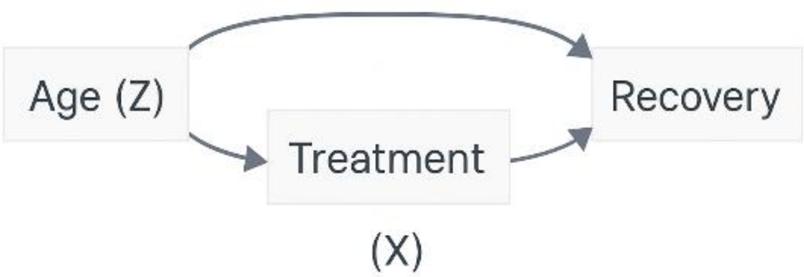

Figure 2: Directed Acyclic Graph (DAG) Representing Causal Relationships Between Age,

Teatment, and Recovery

The variables are binary:

- X: 1 if received Treatment, 0 otherwise.
- Y: 1 if Recovery occurred, 0 otherwise.
- Z: 1 if Older, 0 if Younger.

The variable Age (Z) satisfies the backdoor criterion relative to the effect of X on Y, as it intercepts the only non-causal path between X and Y (X←Z→Y) and is not a descendant of X. Therefore, we can identify the causal effect $\boldsymbol{P(Y = y \mid do(X = x))}$ by adjusting for Z.

Objective: Calculate the Average Causal Effect (ACE) of the treatment on recovery, defined as: $ACE = P(Y = 1 \mid do(X = 1)) - P(Y = 1 \mid do(X = 0))$ (3)

Hypothetical Observational Data: Assume we have the following probabilities estimated from a large sample:

- **Distribution of the confounder (Age):**
  - P(Z=0)=0.6 (Probability of being Younger)
  - P(Z=1)=0.4 (Probability of being Older)
- **Conditional Probability of Recovery given Treatment and Age:**
  - P(Y=1|X=1,Z=0)=0.7
  - P(Y=1|X=1,Z=1)=0.5
  - P(Y=1|X=0,Z=0)=0.4
  - P(Y=1|X=0,Z=1)=0.2

Calculation of the Causal Effect:

We use the adjustment formula (backdoor adjustment):

$$P(Y = y \mid do(X = x)) = \sum P(Y = y \mid X = x, Z = z) P(Z = z) \quad (4)$$

Step 1: Calculate P(Y=1|do(X=1)) Probability of recovery if intervening by assigning the treatment to everyone $P(Y = 1 \mid do(X = 1)) = P(Y = 1 \mid X = 1, Z = 0)P(Z = 0) + P(Y = 1 \mid X = 1, Z = 1)P(Z = 1)$

Substituting the values: $P\big(Y = 1 \mid do(X = 1)\big) = (0.7)(0.6) + (0.5)(0.4)$

$$P\big(Y = 1 \mid do(X = 1)\big) = 0.42 + 0.20$$

$$P(Y = 1 \mid do(X = 1)) = 0.62$$

Step 2: Calculate P(Y=1|do(X=0)) Probability of recovery if intervening by not assigning the treatment to anyone (X=0). $P(Y = 1 \mid do(X = 0)) = P(Y = 1 \mid X = 0, Z = 0)P(Z = 0) + P(Y = 1 \mid X = 0, Z = 1)P(Z = 1)$

Substituting the values: $P\big(Y = 1 \mid do(X = 0)\big) = (0.4)(0.6) + (0.2)(0.4)$

$$P\big(Y = 1 \mid do(X = 0)\big) = 0.24 + 0.08$$

$$P(Y = 1 \mid do(X = 0)) = 0.32$$

Step 3: Calculate the Average Causal Effect (ACE) ACE=P(Y=1|do(X=1))-P(Y=1|do(X=0))

$$ACE = 0.62 - 0.32$$

$$ACE = 0.30$$

Interpretation: The calculation shows that the probability of recovery if the entire population were to receive the treatment would be 62% ($P(Y=1|do(X=1))=0.62$), whereas if no one were to receive it, the probability would be 32% ($P(Y=1|do(X=0))=0.32$).

The Average Causal Effect (ACE) is 0.30. This means that, on average, receiving the treatment increases the probability of recovery by 30 percentage points in this population, after controlling for the confounding effect of Age. This value represents the causal effect of the treatment isolated from the influence of the confounder.

2.2.2 The ladder of causation

Pearl's Ladder of Causation delineates causal inference into three distinct levels. The first level, Association or Passive Observation, represents the foundational tier where traditional machine learning methods are situated. This level pertains to the identification of statistical relationships between observed entities, utilized for training predictive models. In its most rudimentary form, association describes how two observed entities correlate[29].

The second level, Intervention or Acting, transcends mere passive observation. It involves comprehending the impact of changes, and investigating the 'why' behind observed transformations[30].

The third and highest level, Counterfactuals or Imagining What If, embodies the capability to formulate hypotheses regarding what would transpire under altered conditions [31]. Counterfactuals are pivotal for establishing causal relationships, as they enable the simulation of hypothetical scenarios. The placement of this level at the apex of the Ladder of Causation reflects its complexity and significance in advanced causal inference.

3. Materials and Methods

This study adopts a conceptual and formal modeling approach, integrating Causal Artificial Intelligence (Causal AI) with Neutrosophic Logic and Neutrosophic Set Theory to develop a framework for complex decision-making under uncertainty.

3.1 Modeling Framework

The proposed methodology follows three main stages:

Problem Contextualization and Causal Modeling

We define the causal problem space using Directed Acyclic Graphs (DAGs), following the Structural Causal Model (SCM) formalism introduced by Judea Pearl. These graphs capture hypothesized cause-and-effect relationships among variables, enabling the application of causal inference techniques such as backdoor adjustment and do-operations.

Neutrosophic Extension of Causal Inference

To account for indeterminacy, ambiguity, and contradiction in real-world systems, classical probabilities are extended to neutrosophic triplets (T, I, F)—representing the degrees of truth, indeterminacy, and falsity respectively. The standard SCM framework is adapted to a Neutrosophic Structural Causal Model (N-SCM), where causal functions, variables, and interventions are expressed using neutrosophic values and logic.

Simulation and Illustrative Examples

Hypothetical datasets are constructed to illustrate both classical and neutrosophic scenarios. Calculations are carried out using both traditional and neutrosophic versions of the backdoor criterion to estimate the Average Causal Effect (ACE). Simulated interventions are expressed using both standard do-operations and the neutrosophic doN-operator, allowing for the evaluation of outcomes under uncertainty.

This methodological structure provides a novel way to simulate interventions, estimate causal effects, and handle epistemic indeterminacy, making it particularly suitable for applications in Web3 environments, where decentralized decision-making must deal with incomplete, contradictory, or imprecise information.

4. Neutrosophic Causal AI

While traditional Causal AI, with its foundation in structural causal models and the 'do-operation,' provides a robust framework for understanding and simulating causal relationships, it often assumes a level of certainty and precision that is not always present in real-world data.

This limitation becomes particularly salient when dealing with complex systems where information is inherently vague, ambiguous, or contradictory. In such scenarios, the binary logic and precise numerical representations of traditional Causal AI may fail to capture the nuances of uncertainty and indeterminacy. To overcome these limitations, we introduce Neutrosophic Causal AI.

Neutrosophic Causal AI is an extension of Causal AI that seeks to understand cause-and-effect relationships from data (experimental or observational), incorporating neutrosophic logic and set theory to handle uncertainties and indeterminacies. It follows a systematic approach that includes a) problem contextualization, considering inherent uncertainty; b) causal modeling with neutrosophic graphs (DAGs), which represent degrees of truth, falsity, and indeterminacy; c) quantitative validation of causal relationships, considering uncertainty and indeterminacy in the data.

4.1. Ladder of causation in the context of Neutrosophic Causal AI

Like Pearl’s ladder of causation, we have the following steps a) association, b) intervention, c) counterfactuals.

Neutrosophic Association: various traditional machine learning methods have been adapted to the Neutrosophic context [32, 33,34]

Neutrosophic Intervention: the intervention reflected by Judea Pearl's 'do-operation' allows for simulating interventions in causal models (DAGs) by forcing variables to specific values and cutting their incoming edges. This method assumes precise interventions, which often do not match real-world complexity.

Unlike the traditional 'do-operation,' which assigns a single, precise value to a variable, the neutrosophic intervention allows for defining a range of values or a neutrosophic distribution for the intervened variable.

Hypothetically, consider an e-commerce company that seeks to understand the impact of marketing campaigns (A) on product sales (B). The campaigns vary in intensity and segmentation, and external factors (C), such as seasonality and competition, also influence sales. A causal graphic model:

A→B←C

Causal AI employs the 'do-operation' to estimate the impact of campaign intensity (A) on sales (B), while controlling other factors (C).

In practical situations, it may be challenging to accurately control the intensity and segmentation of campaign (A). Furthermore, the company might face uncertainty regarding the campaign's impact on various customer segments.

The neutrosophic intervention do(A=(T=0.8, I=0.1, F=0.1)) represents the company's decision to conduct a campaign with high intensity and segmentation, but with 10% uncertainty about the campaign's execution and a 10% chance that it will not reach the desired target audience.

Neutrosophic counterfactual: Traditional causal AI forms counterfactuals using precise, deterministic values, assuming clear causal relationships. This approach has limitations in complex environments with vague or contradictory information. Neutrosophic counterfactuals, incorporating neutrosophic logic and set theory, allow for representing uncertain scenarios.

Neutrosophic counterfactuals define values of truth, falsity, and indeterminacy rather than assigning precise values to variables. For example, instead of stating 'if the patient had taken drug X, he would have recovered,' it could be expressed as 'if the patient had taken drug X, there is a high chance of recovery, with some uncertainty and a small chance of non-recovery.'

Definition 2. Neutrosophic do-Operator via Neutrosophic Structural Causal Models (N-SCMs)

An alternative formalization conceptualizes the neutrosophic do-operator, denoted $do_N(X = x)$, as an operation performed on a Neutrosophic Structural Causal Model (N-SCM). An N-SCM extends Pearl's SCM framework by allowing components of the model to be represented using neutrosophic entities, explicitly incorporating indeterminacy alongside truth and falsity.

Specifically, an N-SCM,M_N might feature:

a) Structural equations where the functional relationships f˜_i themselves involve neutrosophic logic or map to neutrosophic values: Vi=($\tilde{f}_i pa_i, \tilde{u}_i$)
b) Exogenous variables U˜ whose uncertainty is described by neutrosophic probability distributions $P_N(u) = (T, I, F)$.

In this context, the neutrosophic intervention $do_n(X = x)$ parallels the standard do-operation by modifying the structure of the $M_N$into a submodel $M_{N,x}$:

1. The neutrosophic structural equation(s) determining X within M_N are removed.
2. The variable X is assigned the value x (which could potentially also be a neutrosophic value x˜ in some formulations).

3. All other neutrosophic structural equations and the neutrosophic distributions P_N(u) governing the exogenous variables remain unchanged.

The outcome of this operation is the neutrosophic probability distribution (or neutrosophic value set) of an outcome variable Y in the modified model $M_{N,x}$. This is denoted $P_N(Y = y \mid do_N(X = x))$ and is calculated by propagating the inputs (including the intervention $X = x$ and the neutrosophic exogenous uncertainties $P_N(u)$) through the neutrosophic functions $\tilde{f}$ of the submodel $M_{N,x}$ using the appropriate rules of neutrosophic logic and probability calculus:

$$P_N(Y = y \mid do_N(X = x)) \triangleq P_{M_{N,x}}(Y = y) \quad (5)$$

This definition emphasizes the do_N-operator as a mechanism to compute causal effects by simulating interventions directly within a causal model whose fundamental components explicitly encode indeterminacy (I) alongside truth (T) and falsity (F), thus providing predictions $P_N(Y = y \mid do_N(X = x)) = (T, I, F)$ that reflect this inherent systemic ambiguity.

Definition 3 [35, 36]: Neutrosophic Multiplication Operator (⊗)

For two neutrosophic probabilities $A = (T_A, I_A, F_A)$ and $B = (T_B, I_B, F_B)$, where $T, I,$ and F represent the truth, indeterminacy, and falsity components respectively, the neutrosophic multiplication operator $\otimes$ is defined as:

$$A \otimes B = (T_A \times T_B, I_A + I_B - I_A \times I_B, F_A + F_B - F_A \times F_B) \quad (6)$$

Where:

- $T_A \times T_B$ represents the product of truth components
- $I_A + I_B - I_A \times I_B$ represents the product of indeterminacy components
- $F_A + F_B - F_A \times F_B$ represents the product of falsity components

This operation extends the classical probability multiplication to the neutrosophic domain, preserving the interpretation that when two independent events are considered jointly, their probability components are multiplied independently.

Definition 4 [36, 37]: Neutrosophic Addition Operator (⊕)

For two neutrosophic probabilities $A = (T_A, I_A, F_A)$ and $B = (T_B, I_B, F_B)$, the neutrosophic addition operator $\oplus$ is defined as:

$$A \oplus B = (T_A + T_B - T_A \times T_B, I_A \times I_B, F_A \times F_B) \quad (7)$$

Where:

- $T_A + T_B - T_A \times T_B$ represents the probability union formula applied to truth components
- $I_A \times I_B$ represents the probability union formula applied to indeterminacy components

- $F_A \times F_B$ represents the probability union formula applied to falsity components

This operation generalizes the classical probability union formula $P(A \cup B) = P(A) + P(B) – P(A \cap B)$ to the neutrosophic context, accounting for all three dimensions of neutrosophic information.

Definition 5[36,37]: Neutrosophic Subtraction Operator $\ominus$

For two neutrosophic probabilities $A = (T_A, I_A, F_A)$ and $B = (T_B, I_B, F_B)$, the neutrosophic subtraction operator $\ominus$ is defined as:

$A \ominus B = A \otimes B^c$ (8)

Where:

$A \otimes B^c = \left(T_A \times (1 - T_B), I_A + (1 - I_B) - I_A \times (1 - I_B), F_A + (1 - F_B) - F_A \times (1 - F_B)\right) = \left(T_A \times (1 - T_B), I_A + (1 - I_A) \times (1 - I_B), F_A + (1 - F_A) \times (1 - F_B)\right)$

The neutrosophic subtraction operator is particularly important for calculating causal effects in neutrosophic environments, such as the Neutrosophic Average Causal Effect (ACE_N).

Example 2 (Neutrosophic Adaptation): Calculation of Neutrosophic Causal Effect

Scenario: We revisit the observational study scenario evaluating a Treatment (X) on Recovery (Y), with Age (Z) as a confounder. The causal structure (DAG) remains the same (Figure 2).

Variables are binary $(X, Y, Z \in \{0,1\})$. We again aim to adjust for Z using the backdoor criterion. However, we now assume our knowledge about the system probabilities involves indeterminacy, represented by neutrosophic probabilities $P_N N = (T, I, F)$, where T is the degree of truth, I is the degree of indeterminacy, and F is the degree of falsity.

Objective: Estimate the neutrosophic causal effect of the treatment on recovery, specifically by calculating $P_N(Y = 1 \mid do_N(X = 1))$ and $P_N(Y = 1 \mid do_N(X = 0))$, where do_N represents the intervention concept within this neutrosophic context. We can then examine the difference, particularly in the truth component (T).

Hypothetical Neutrosophic Observational Data: Assume the following neutrosophic probability estimates:

- **Distribution of the confounder (Age):**
  - $P_{N(Z=0)} = (0.6, 0.1, 0.3)$ (Younger)
  - $P_{N(Z=1)} = (0.4, 0.1, 0.5)$ (Older)
- **Conditional Neutrosophic Probability of Recovery (Y=1):**
  - $P_N(Y = 1 \mid X = 1, Z = 0) = (0.70, 0.20, 0.10)$
  - $P_N(Y = 1 \mid X = 1, Z = 1) = (0.50, 0.30, 0.20)$
  - $P_N(Y = 1 \mid X = 0, Z = 0) = (0.40, 0.15, 0.45)$
  - $P_N(Y = 1 \mid X = 0, Z = 1) = (0.20, 0.25, 0.55)$

Calculation of the Neutrosophic Causal Effect:

We adapt the adjustment formula to compute the resulting neutrosophic probability (T, I, F).

Step 1: Calculate $\boldsymbol{P_N(Y=1 \mid do_N(X=1)) = (T_1, I_1, F_1)}$ Neutrosophic probability of recovery if intervening by assigning treatment X=1 to everyone.

$P_N(Y=1 \mid X=1, Z=0) \otimes P(Z=0) \oplus P_N(Y=1 \mid X=1, Z=1) \otimes P(Z=1)$=

(0.70,0.20,0.10) $\otimes$ (0.6,0.1,0.3) $\oplus$ (0.50,0.30,0.20) $\otimes$ (0.4,0.1,0.5)= (0.536, 0.1036, 0.222)

Result for $\boldsymbol{P_N\big(Y=1 \mid do_N(X=1)\big)}$ = (0.536, 0.1036, 0.222)

Step 2: Calculate $\boldsymbol{P_N(Y=1 \mid do_N(X=0)) = (T_0, I_0, F_0)}$ Neutrosophic probability of recovery if intervening by assigning control $X=0$ to everyone.

$$P_N(Y=1 \mid X=0, Z=0) \otimes P(Z=0) \oplus PN(Y=1 \mid X=0, Z=1) \otimes P(Z=1) =$$

(0.40,0.15,0.45) $\otimes$ (0.6,0.1,0.3) $\oplus$ (0.20,0.25,0.55) $\otimes$ (0.4,0.1,0.5)= (0.3008, 0.076375, 0.476625)

Result for $\boldsymbol{P_N(Y=1 \mid do_N(X=0))}$= (0.3008, 0.076375, 0.476625)

Step 3: Examine the Neutrosophic Average Causal Effect (ACE)

$$ACE_N = \boldsymbol{P_N\big(Y=1 \mid do_N(X=1)\big)} \ominus \boldsymbol{P_N\big(Y=1 \mid do_N(X=0)\big)}$$
$$= |(0.536, 0.1036, 0.222) \ominus (0.3008, 0.076375, 0.476625)|$$
$$= (0.3747712, 0.9315151, 0.62918575)$$

Interpretation: The neutrosophic analysis yielded a result of (0.3748,0.9315,0.6292), which provides a multidimensional interpretation of the causal effect. Similar to traditional Average Causal Effect (ACE) analysis, the truth component (T=0.3748) indicates a positive causal effect of the treatment on recovery likelihood. However, the neutrosophic approach offers richer insights by explicitly quantifying the significantly high indeterminacy (I=0.9315) associated with the predicted outcomes, acknowledging a very large degree of inherent uncertainty, ambiguity, or vagueness in the causal prediction under this specific definition. Additionally, the falsity component (F=0.6292) represents a considerable degree to which the causal effect may not be present or the premises leading to recovery are false. While conventional models provide only single-point probability estimates that implicitly assume zero indeterminacy, the neutrosophic model, even with this particular operator definition, aims to capture the ambiguity inherent in scenarios involving vague or incomplete information, potentially offering a more realistic, albeit in this case highly uncertain, assessment.

5. Applications of Neutrosophic Causal AI in Web3 with Blockchain-AI Integration

The convergence of blockchain technology and artificial intelligence presents transformative potential, particularly for creating smarter, more autonomous, and trustworthy decentralized applications (dApps) within the Web3 ecosystem. While integrating traditional AI offers benefits like analyzing on-chain data for patterns, its reliance on correlation often falls short in complex, dynamic Web3 environments where understanding true cause-and-effect is crucial for security, governance, and economic stability. Furthermore, real-world data feeding into Web3 systems via oracles, or generated through decentralized interactions, is frequently characterized by inherent uncertainty, ambiguity, and potential contradiction—limitations that traditional Causal AI, assuming precision, struggles to address adequately. Neutrosophic Causal AI emerges as a critical enabler in this context, providing the necessary tools to model causality rigorously while explicitly managing indeterminacy.

One key application lies in enhancing Smart Contracts and Oracle Integration[38]. Smart contracts automate agreements based on predefined conditions, often triggered by external data provided by oracles. However, oracle data can be noisy, delayed, derive from sources with varying reliability, or represent inherently ambiguous states. Neutrosophic Causal AI allows oracles to report data not as single crisp values, but as neutrosophic triplets $(\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F})$, quantifying the data's perceived truthfulness, indeterminacy (e.g., due to source disagreement or measurement uncertainty), and falsity. Smart contracts equipped with N-SCMs can then ingest this neutrosophic data and reason causally under uncertainty. For instance, a decentralized insurance contract could use an N-SCM to assess crop failure risk based on neutrosophic weather data from multiple oracles. Using the $\boldsymbol{do_N}$-operator, it could simulate the causal effect of specific weather patterns (represented neutrosophically) on yield likelihood $\boldsymbol{P_N}\left(\boldsymbol{Yield}\middle|\boldsymbol{do_N}(\boldsymbol{Weather} = (\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F}))\right)$, making payout decisions based not just on the estimated truth $(\boldsymbol{T})$ of crop failure but also considering the level of indeterminacy $(\boldsymbol{I})$. This allows for more robust and fair automated decisions that explicitly acknowledge data imperfections.

Another vital area is Decentralized Governance, particularly within Decentralized Autonomous Organizations (DAOs). DAOs rely on collective decision-making for protocol upgrades, treasury management, and strategic direction, often based on proposals with complex and uncertain consequences. Voters face incomplete information, potentially biased analyses, and conflicting expert opinions. Neutrosophic Causal AI can provide decision support by modeling the potential causal impacts of a proposal $(\boldsymbol{X})$ on key DAO health metrics $(\boldsymbol{Y})$, e.g., token value, user engagement, and protocol security. Expert opinions or simulation results regarding impacts could be encoded as neutrosophic probabilities $\boldsymbol{P_N}(\boldsymbol{Y}|\boldsymbol{do_N}(\boldsymbol{X} = \boldsymbol{proposal})) = (\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F})$. By comparing the neutrosophic outcomes of implementing the proposal versus maintaining the status quo, N-Causal AI can present voters with a clearer picture that includes not only the likely effect $(\boldsymbol{T})$ but also the degree of residual uncertainty or disagreement $\boldsymbol{I}$ This explicit representation of indeterminacy fosters more informed and transparent collective decision-making, aligning with the democratic ethos of DAOs.

Furthermore, Neutrosophic Causal AI offers significant advantages in Decentralized Finance (DeFi) for Risk Assessment and Management. DeFi protocols, such as lending platforms or automated market makers, operate in highly volatile environments and are susceptible to complex risks like cascading liquidations, impermanent loss, or economic exploits. Traditional risk models often struggle with the unprecedented nature of these systems and the ambiguity of market signals. N-Causal AI can build more resilient risk models by constructing N-SCMs that map causal relationships between factors like market volatility, collateralization ratios, oracle price feed deviations, and protocol parameters, representing uncertain factors (e.g., market sentiment, likelihood of exploit) neutrosophically. The $\boldsymbol{do_N}$-operator allows for sophisticated stress testing, simulating the impact of extreme events $\boldsymbol{do_N}(\boldsymbol{MarketShock} = (\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F}))$ on protocol stability. The resulting risk assessments presented as $(\boldsymbol{T}, \boldsymbol{I}, \boldsymbol{F})$ for outcomes like "Liquidation Cascade Likelihood," provide a more nuanced understanding than single probability scores, enabling better-informed parameter tuning and user protection mechanisms.

Finally, the integration of N-Causal AI aligns strongly with the core Web3 principles of Transparency and Auditability. While blockchain ensures data immutability, the logic of AI models operating on that data can remain opaque. By requiring the explicit definition of causal relationships within an N-SCM (which could potentially be stored or referenced on-chain), Neutrosophic Causal AI makes the reasoning process more transparent. Stakeholders can inspect the assumed causal structure and how indeterminacy is handled, fostering greater trust compared to black-box AI models. This explicit causal representation, acknowledging $\boldsymbol{T}, \boldsymbol{I}$, and $\boldsymbol{F}$, provides a foundation for building truly robust, verifiable, and ethically considerate AI-driven systems within the decentralized web.

6. Conclusions

Neutrosophic Causal AI represents a significant leap forward in the development of intelligent systems capable of operating effectively in real-world environments characterized by uncertainty, vagueness, and contradiction. Its value lies not only in enhancing predictive accuracy but in elevating the epistemic quality of AI-based decisions by incorporating explicit degrees of truth, falsity, and indeterminacy into the causal reasoning process.

By integrating the neutrosophic framework with structural causal modeling, this approach extends the boundaries of conventional Causal AI, allowing for the formalization of ambiguous or contradictory causal relationships that would otherwise be dismissed or misrepresented. The proposed Neutrosophic do-operator and the construction of Neutrosophic Structural Causal Models (N-SCMs) provide a robust mathematical apparatus to simulate interventions, quantify causal effects, and represent systemic ambiguity, all within a consistent logical foundation.

In the context of Web3 ecosystems, where trust, decentralization, and transparency are paramount, Neutrosophic Causal AI adds a layer of interpretability and resilience to AI-driven decisions. Smart contracts, DAOs, and decentralized finance (DeFi) mechanisms can benefit from decision protocols that are not only technically efficient but epistemologically reflexive, accommodating multiple possible truths and modeling the nuances of human and institutional behavior under incomplete information.

Moreover, this framework opens new avenues for transdisciplinary research, intersecting artificial intelligence, formal logic, decision theory, and philosophy of technology. It encourages the development of ethically aware and socially responsible AI, especially in sensitive domains such as public governance, collective decision-making, and risk management.

As decentralized infrastructures and autonomous agents proliferate, Neutrosophic Causal AI emerges as a foundational component for building intelligent, fair, and transparent systems. By embracing complexity and modeling what is traditionally excluded—the indeterminate and the contradictory—this approach lays the groundwork for a new generation of algorithms capable of navigating the ambiguities of the real world with integrity and nuance.

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