Plural Logics and Artificial Intelligence: A Neutrosophic Approach to Causal Analysis

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Abstract

This article proposes a framework of logical pluralism applied to causal analysis in artificial intelligence (AI) and social sciences. Grounded in the pluralist thesis that there is no single monolithic concept of causation, but rather a family of related concepts, we confront the Humean premise that "we do not observe causation' with Anscombe's counter-argument that we do, in fact, perceive causal actions such as pushing, striking, and cutting. Building on this foundation, we present an illustrative study comparing crisp-set Qualitative Comparative Analysis (csQCA), fuzzy-set QCA (fsQCA), and neutrosophic QCA (nQCA). From this comparison, we derive both the methodological and substantive implications.
Methodologically, we find that: (i) strict dichotomization (csQCA) can underestimate causal relationships; (ii) graded membership (fsQCA) more effectively captures empirical strength and relevance; and (iii) neutrosophic decomposition (nQCA) explicitly accounts for truth, indeterminacy, and falsity, thereby offering a pluralistic diagnosis of the causal relationship. We further enrich this analysis by incorporating a pluralistic view of causality, encompassing mechanical production, counterfactual difference, capacities/dispositions, and mechanisms.
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1. Introduction

Logical pluralists contend that there is no unified concept of causation. Instead, they argue for a plurality of related concepts, all falling under the umbrella term "causation" [1], [2]. This perspective directly challenges the fundamental premise of David Hume's influential critique of causality–the assertion that causation is not something we can observe in the world. In contrast, G.E.M. Anscombe famously argued that we do, in fact, observe causation in a multitude of everyday actions and processes. We see things being pushed, struck, or cut. In what sense can it be claimed that we do not observe causation? The Humean response would be that what we truly observe are mere constant conjunctions and regular successions of events, not the elusive "necessary connection' that binds cause to effect.

To this end, the pluralist replies that there are multiple equally legitimate notions of causality. These include but are not limited to counterfactual differences, production and processes, underlying mechanisms, and inherent capacities or dispositions. Within some of these conceptual frameworks, we can have direct perceptual or cognitive access to causal relationships, at least in ordinary contexts.

In the fields of artificial intelligence and social sciences, this debate is far from purely a metaphysical exercise. This has profound implications for how we model, infer, and communicate causal relationships. The increasing complexity of AI systems, particularly those that interact with and make decisions regarding the social world, demands a more sophisticated and nuanced approach to causal reasoning. The central thesis of this article is twofold: (1) logical pluralism, as articulated by Beall and Restall [5] and Russell [2], advises the use of different logical frameworks depending on the specific task and domain; and (2) causal pluralism, as championed by Cartwright [1], Woodward [3], Salmon [4], and Lewis

[6], suggests that different concepts of causality can illuminate complementary facets of the same phenomenon. We argue that by embracing both logical and causal pluralism, we can develop more robust, transparent, and explainable AI systems that are better equipped to handle real-world complexities and uncertainties.

2. Preliminaries

The history of formal logic has been largely dominated by what can be termed logical monism, the belief in a single, universally correct system of logical reasoning. This tradition, which can be traced from Aristotle through Frege and Russell's foundational work, established classical propositional and predicate logic as the gold standard for rational thought [4]. The elegance and power of classical logic, with its well-defined syntax, semantics, and proof theory, make it an attractive framework for formalizing human reasoning. In the context of artificial intelligence, this monistic approach manifests as an almost exclusive reliance on classical logic for knowledge representation and reasoning. Early AI systems, from expert systems such as MYCIN and DENDRAL to automated theorem provers, were built based on the fundamental assumption that intelligent reasoning can be effectively captured and replicated through the operations of classical logic. This approach, often referred to as "Good Old-Fashioned AI" (GOFAI), has achieved considerable success in well-defined closed-world domains. However, they also face significant challenges when confronted with the complexities and uncertainties of the real world.

The emergence of logical pluralism presents a significant challenge for this long-standing monistic orthodoxy. Pioneered by philosophers, such as J.C. Beall and Greg Restall, logical pluralism posits that there is more than one correct logic. In this view, the appropriateness of a given logical system is contingent upon the specific context and purpose of the reasoning task [5].

According to logical pluralism, different notions of logical validity arise from different conceptions of what constitutes a "case" or a "model" [5], [6]. In the realm of artificial intelligence, this perspective provides a robust justification for the employment of a diverse array of non-classical logic, including temporal, epistemic, non-monotonic, paraconsistent, and neutrosophic logic. Each of these logical systems is tailored to handle specific types of reasoning that are often intractable to classical logic, such as reasoning about time, knowledge, belief revision, contradictory information, and indeterminacy.

Parallel to logical pluralism, the notion of causal pluralism suggests that a variety of conceptual families of causality coexist. These include:

1. **Counterfactual Difference:** This view, associated with thinkers like David Lewis [6], Judea Pearl [7], and James Woodward [3], defines cause as something that makes a difference to the effect. In other words, if the cause did not occur, then the effect would not have occurred.
2. **Production and Processes:** This perspective, championed by Wesley Salmon [4], focuses on the physical processes and transmission of energy and information that connect a cause to its effect.
3. **Mechanisms:** This approach, articulated by Machamer et al. [8], identifies the underlying mechanisms and interacting parts that produce a phenomenon.
4. **Capacities and Dispositions:** Nancy Cartwright [1] argues that causes have capacities or dispositions to produce effects that may or may not be exercised in a given situation.
5. **Configurational/INUS Conditions:** This view, developed by Mackie [9] and advanced by Ragin [10] in the context of social science methodology, understands the cause as an Insufficient but Necessary part of an Unnecessary but Sufficient condition for an effect.
6. **Interventionism:** Closely related to counterfactual and mechanistic approaches, the interventionist account, most notably formulated by James Woodward [3], defines a cause as a variable that can be manipulated to bring about a change in another variable.

Each of these conceptualizations of causality is designed to answer different kinds of questions: why an event occurred, how it came about, under what interventions it would change, and what components were involved. Pluralism, it is important to note, is not a form of relativism. Rather, it proposes an ecology of concepts and evidential standards, with at least partial translations and integrations possible between different frameworks.

3. Illustrative Study: csQCA, fsQCA, and nQCA

To demonstrate the practical implications of logical pluralism in causal analysis, we present an illustrative study comparing three Qualitative Comparative Analysis (QCA) methods: crisp-set QCA (csQCA), fuzzy-set QCA (fsQCA), and neutrosophic QCA (nQCA). QCA was first developed by sociologist Charles Ragin in the late 1980 [10] s as a way to bridge the gap between qualitative case-oriented research and quantitative variable-oriented research. It is a set-theoretic method that is particularly well-suited for analyzing causal complexity, including issues of equifinality (multiple causal paths to the same outcome) and conjunctural causation (causes that only produce an effect in combination with other causes). Over the past three decades, QCA has become an increasingly popular method in social sciences, and it is now beginning to gain traction in other fields, including public health, policy analysis, and computer science.

3.1 Crisp-set QCA (csQCA)

In a crisp-set QCA, both the causal conditions and outcome are represented as binary variables, with cases having either full membership (1) or no membership (0) in a given set. The analysis then proceeded to identify logical relationships between these sets. The two key parameters in csQCA are consistency and coverage.

Consistency measures the degree to which a causal condition or a combination of conditions is a subset of outcomes. In other words, it assesses the extent to which evidence supports the claim that the cause leads to the outcome. The formula for consistency in csQCA is

$$Consistency_{cs}\,(X \Rightarrow Y) = \frac{(\Sigma\,(X_i \wedge Y_i))}{(\Sigma\,X_i)} \qquad (1)$$

Coverage measures the empirical relevance of a causal condition or combination of conditions. It assesses the extent to which the outcome is explained by cause. The formula for coverage in csQCA is

$$Coverage_{cs}(X \Rightarrow Y) = \frac{(\Sigma\,(X_i \wedge Y_i))}{(\Sigma\,Y_i)} \qquad (2)$$

3.2 Fuzzy-set QCA (fsQCA)

Fuzzy-set QCA is an extension of csQCA that allows for partial membership in sets. Instead of binary values, cases can have membership scores ranging from 0 to 1. This allows for a more fine-grained analysis of causal relationships as it can account for graded and partial effects. The formulas for consistency and coverage in the fsQCA are as follows:

$$\mathrm{consistency_{fs}}\,(X_i \le Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum X_i} \qquad (3)$$

$$\mathrm{coverage_{fs}}\,(X_i \le Y_i) = \frac{\sum \min(X_i, Y_i)}{\sum Y_i} \qquad (4)$$

3.3 Neutrosophic QCA (nQCA)

Neutrosophic QCA is a further extension of QCA that incorporates the concept of indeterminacy [11]. In nQCA, each case is represented by a neutrosophic triple (T, I, F), where T represents the degree of truth membership, I the degree of indeterminacy, and F the degree of falsity membership. This allows for a more nuanced analysis of causal relationships as it can explicitly account for uncertainty and ambiguity in the data.

Consistency and coverage in nQCA are generalized using a neutrosophic implication operator, which operates component-wise on triples [12]. This extension captures not only how strongly a condition implies an outcome (truth), but also the degree to which the relationship remains ambiguous (indeterminacy) or is contradicted by evidence (falsity). The formulae for neutrosophic consistency and coverage are:

$$Consistency_N(X \Rightarrow Y) = \frac{1}{n}\sum_{i=1}^{n} I_R(X_i \Rightarrow Y_i) \in [0,1]^3 \quad (5)$$

$$Coverage_N(X \Rightarrow Y) = \frac{1}{n}\sum_{i=1}^{n} I_R(Y_i \Rightarrow X_i) \in [0,1]^3 \quad (6)$$

where I_R returns a triple value (T, I, F). Thus, the measures of consistency and coverage are no longer single scalars but vectors of three components (T, I, F) that explicitly represent truth, uncertainty, and falsity in causal relations.

4. Illustrative Example

To make the comparison between csQCA, fsQCA, and nQCA more concrete, we will now discuss an illustrative example. We will study the implication X => Y for the three cases using the same dataset for each method.

4.1 Dataset

The fuzzy memberships for our three cases are as follows:

- **Case 1:** X1 = 0.8, Y1 = 0.9
- **Case 2:** X2 = 0.6, Y2 = 0.5
- **Case 3:** X3 = 0.7, Y3 = 0.4

The neutrosophic memberships for the same cases are:

- **Case 1:** X1 = (0.8, 0.1, 0.1), Y1 = (0.9, 0.05, 0.05)
- **Case 2:** X2 = (0.6, 0.2, 0.2), Y2 = (0.5, 0.3, 0.2)
- **Case 3:** X3 = (0.7, 0.2, 0.1), Y3 = (0.4, 0.4, 0.2)

4.2 Crisp-set QCA (csQCA)

For csQCA, we first binarized the fuzzy membership scores. A common rule for binarization is to assign a value of 1 if the membership score is greater than 0.5, and 0 otherwise. Applying this rule to our dataset, we obtain

- **Case 1:** X1 = 1, Y1 = 1
- **Case 2:** X2 = 1, Y2 = 0
- **Case 3:** X3 = 1, Y3 = 0

Now, we can calculate the consistency and coverage:

- $\boldsymbol{sum(X_i and\, Y_i)}$: 1 (only Case 1)
- $\boldsymbol{sum(X_i)}$**:** 3
- $\boldsymbol{sum(Y_i)}$**:** 1
- $\boldsymbol{Consistency_{cs}}$**:** 1 / 3 = 0.33
- $\boldsymbol{Coverage_{cs}}$**:** 1 / 1 = 1.00

The csQCA analysis showed a very low consistency score of 0.33. This is because there are two counterexamples (Cases 2 and 3) in which the cause is present (X=1), but the outcome is absent (Y=0). However, the coverage score is 1.00, which means that the single case in which both the cause and outcome are present (Case 1) covers all cases in which the outcome is present.

4.3 Fuzzy-set QCA (fsQCA)

For fsQCA, we used the original fuzzy membership scores. First, we calculated the minimum X and Y membership scores for each case.

- **Case 1:** min(0.8, 0.9) = 0.8
- **Case 2:** min(0.6, 0.5) = 0.5
- **Case 3:** min(0.7, 0.4) = 0.4

Next, we calculate the sum of the minima, the sum of the X scores, and the sum of the Y scores:

- **sum(min):** 0.8 + 0.5 + 0.4 = 1.7
- **sum(X):** 0.8 + 0.6 + 0.7 = 2.1
- **sum(Y):** 0.9 + 0.5 + 0.4 = 1.8

Finally, we can calculate the consistency and coverage:

- $\boldsymbol{Consistency_{fs}}$: 1.7 / 2.1 = 0.81
- $\boldsymbol{Coverage_{fs}}$: 1.7 / 1.8 = 0.94

By allowing partial membership, the fsQCA analysis softens the crisp contradictions found in the csQCA analysis. The result is a much stronger consistency score of 0.81 and a high coverage score of 0.94, suggesting a strong and empirically relevant causal relationship.

4.4 Neutrosophic QCA (nQCA)

For nQCA, we use neutrosophic membership. We use a component-wise neutrosophic implication operator defined as [13]:

The chosen Neutrosophic R-implication Equation is:

$$\mathrm{t}_{\Rightarrow_{\mathrm{NL}}} = \begin{cases} 1, \text{if } \mathrm{t_x} \le \mathrm{t_y} \\ 1 - \mathrm{t_x} + \mathrm{t_y}, \text{otherwise} \end{cases}, \ \mathrm{i}_{\Rightarrow_{\mathrm{NL}}} = \begin{cases} 0, \text{if } \mathrm{i_y} \le \mathrm{i_x} \\ \mathrm{i_y} - \mathrm{i_x}, \text{otherwise} \end{cases}, \text{ and } \mathrm{f}_{\Rightarrow_{\mathrm{NL}}} = \begin{cases} 0, \text{if } \mathrm{f_y} \le \mathrm{f_x} \\ \mathrm{f_y} - \mathrm{f_x}, \text{otherwise} \end{cases} \quad (7)$$

It is the so-called Lukasiewicz's Neutrosophic R-implication.

Applying this operator to each case for consistency (X => Y), we obtain

- **Case 1:** (1, 0, 0)
- **Case 2:** (0.9, 0.1, 0)
- **Case 3:** (0.7, 0.2, 0.1)

The mean of these triples gives us the neutrosophic consistency:

- $\boldsymbol{Consistency_N}$: (0.8667,0.1,0.0333)

Applying the operator to each case for coverage (Y => X), we obtain

- **Case 1:** (0.9, 0.05, 0.05)
- **Case 2:** (1, 0, 0)
- **Case 3:** (1, 0, 0)

The mean of these triples gives us the neutrosophic coverage:

- $\boldsymbol{Coverage_N}$: (0.9667, 0.0167, 0.0167)

The nQCA decomposes the assessment of the causal relationship into three components: truth (T), indeterminacy (I), and false (F). The resulting Neutrosophic Consistency is (0.8667,0.1000,0.0333), which reveals a high truth component in the causal implication (X⟹Y), backed by low indeterminacy and minimal falsity. Furthermore, the Neutrosophic Coverage is (0.9667,0.0167,0.0167), demonstrating that condition X has an almost complete explanatory power over the occurrence of outcome Y, with extremely low values for both indeterminacy and falsity. Together, these metrics provide an exceptionally robust and clear picture of the sufficiency relationship, significantly overcoming the ambiguity limitations inherent in the traditional scalar QCA methods.

Table 1. Comparison of consistency and coverage measures in csQCA, fsQCA, and nQCA

Method	Consistency	Coverage
csQCA	0.33	1.00
fsQCA	0.81	0.94
nQCA	(0.8667,0.1,0.0333)	(0.9667, 0.0167, 0.0167)

csQCA, with its strict dichotomization, is fragile and can easily lead to the conclusion that there is no causal relationship. By allowing for gradations, the fsQCA strengthens the relationship and provides a more realistic assessment. nQCA further disentangles the relationship into truth, uncertainty, and falsity, which aligns with the principles of logical pluralism and provides a more transparent and comprehensive handling of ambiguity.

5. Discussion

The comparison of csQCA, fsQCA, and nQCA in our illustrative example offers several important insights for causal analysis in AI and social sciences. These insights can be grouped into five key categories. Each of these areas is explored in greater detail in the following subsections, with a particular focus on the practical implications for designing and implementing more robust and trustworthy AI systems.

1. Calibration and Sensitivity: The dramatic difference between the consistency scores of csQCA (0.33) and fsQCA (0.81) highlights the critical role of calibration in causal analysis. The choice of a threshold for dichotomization can fundamentally alter the causal verdict. This suggests that researchers should perform sensitivity analyses of their calibration decisions and report the stability of their findings across different logical systems.

2. Multi-logic Robustness: The convergence between the fsQCA consistency score (0.81) and the truth component of the nQCA consistency score (0.8667) provides strong support for the robustness of the finding that there is a difference-making relationship between X and Y. The divergence in the indeterminacy component of the nQCA score (0.1), however, advises caution and suggests that researchers should explicitly report the level of uncertainty in their findings.

3. Uncertainty Management: The indeterminacy component of the nQCA score provides a valuable tool for managing epistemic risk. This allows researchers to make more informed decisions about, for example, whether to raise the criteria for confirmation, collect additional data, or condition their recommendations on the level of uncertainty.

4. Contradiction Diagnosis: The falsity component of the nQCA score (0.0333) suggests that there are limited but real contradictions in the data. This invites further exploration of potential subgroups, contextual conditions, and latent mechanisms that may block the efficacy of X in some cases.

5. Communication and Traceability: The plurality of metrics offered by nQCA enhances the explainability of causal findings. It allows researchers to communicate not only "how strong" the relationship between X and Y is, but also "how indeterminate" and "how contradictory" the observed pattern is.

Under the capacity/disposition notion of causality, the indeterminacy component in nQCA indicates that the causal capacity of X exists, but its activation is context-dependent. This requires specifying the modulators and boundary conditions that govern this relationship [1]. Under a configurational/INUS notion of causality, the pattern is consistent with conjunctural causation and equifinality: X may be a necessary part of certain sufficient combinations but not universally sufficient on its own.

This conceptual multiverse is not a defect but an epistemic advantage. This allows for the integration of information about the strength, stability, mechanism, and context of a causal relationship.

5.1 Implications for Artificial Intelligence

The insights from our illustrative study have several important implications for AI development.

- **Neuro-symbolic Architectures:** Neuro-symbolic AI systems can benefit from the use of multiple logics (e.g., temporal, deontic, paraconsistent, and neutrosophic) at different stages of the processing pipeline (e.g., perception, verification, and explanation) [11], [12].
- **Automated Causal Evaluation:** Adopting inter-logic cross-validation in automated causal evaluation can reduce the risk of spurious decisions owing to calibration artifacts.

- **Responsible AI Communication:** Responsible AI communication should explicitly report the truth, indeterminacy, and falsity components of causal claims when pertinent.
- **Methodological Triangulation:** Integrating QCA with causal graphs (Pearl) and interventionist tests (Woodward) offers pluralistic triangulation of differences, mechanisms, and configurations.

6. Conclusion

The illustrative study at the heart of this article demonstrates that the joint application of csQCA, fsQCA, and nQCA does not produce "three truths," but rather three compatible projections of the same causal phenomenon. These projections reveal a causal relationship characterized by high difference-making strength, nontrivial indeterminacy, and bounded contradiction. This exemplifies logical pluralism, in that different logical systems are valid depending on the chosen notions of case and validity, and causal pluralism, in that different legitimate concepts of causality can be brought to bear on the same phenomenon.

The practical consequence of this is clear: to model complex phenomena and to design explainable and robust AI, we must learn to inhabit this plurality rather than collapse it into a single monolithic verdict. The future of AI, particularly its application to complex social and scientific problems, will depend on its ability to embrace and manage the inherent ambiguities and uncertainties of the world. As outlined in this article, a pluralistic approach to logic and causality provides a promising path.

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