TEACHING TO MEASURE DOUBT WITH ARTIFICIAL INTELLIGENCE: An Educational Proposal to Analyze the Causes of Violence in Guayaquil from Indeterminacy and Uncertainty

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ABSTRACT

The growing complexity of social phenomena, such as urban violence in Guayaquil, overwhelms traditional analytical frameworks that tend to privilege unicausal explanations and suppress uncertainty. This article presents an innovative educational proposal that uses a neutrosophic epistemic evaluation framework, implemented through large language models (LLMs), to teach students and citizens to measure and visualize doubt, indeterminacy, and conflict in the analysis of social problems. The proposed model decomposes causal propositions into three independent dimensions: Truth (T), Indeterminacy (I), and Falsity (F), allowing the coexistence of contradictory evidence (hyper-truth) and epistemic abstention as a valid response to structural ignorance. We present a case study with 75 participants in Guayaquil, where we evaluated the impact of the model on their perception of the causes of local violence. Results demonstrate significant cognitive change: 77.4% of participants transitioned from binary thinking to a more complex and nuanced understanding of the problem. Quantitative analysis of neutrosophic perceptions (T, I, F) reveals low correlation between dimensions, empirically validating the theoretical independence of the framework. We conclude that this approach not only offers a more honest analytical tool for social research but also constitutes a powerful pedagogical strategy for cultivating critical thinking, epistemic humility, and a citizenry better prepared to navigate 21st-century uncertainty.

Keywords: Critical Thinking, Neutrosophy, Artificial Intelligence, Education for Uncertainty, Urban Violence, Causal Analysis, Epistemic Evaluation, Large Language Models, Indeterminacy

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1. INTRODUCTION

Contemporary society faces an avalanche of "wicked problems," characterized by complexity, interdependence, and resistance to simple solutions (Rittel & Webber, 1973; Head & Alford, 2015). Urban violence, particularly in cities like Guayaquil, Ecuador, is an archetype of such a challenge. Despite abundant data and analysis, public and academic discourse often oscillates between simplistic and polarized narratives: violence is a problem of poverty, drug trafficking, family disintegration, or institutional weakness. Each of these explanations, while partially true, proves insufficient in isolation and contributes to a cycle of reactive and often ineffective public policies (Muggah, 2015; UNODC, 2019).

The fundamental problem is not a lack of information but a lack of conceptual and pedagogical tools to process contradictory, incomplete, and ambiguous information. Traditional educational frameworks, anchored in a bivalent epistemology of true/false, inadequately prepare citizens and future professionals to navigate the inherent uncertainty of complex social systems (Barnett, 2004; King & Kitchener, 2004). In this context, the central question motivating our research is: **How can we teach students to measure, visualize, and constructively dialogue with doubt and uncertainty when analyzing social problems?**

This article proposes an answer through the convergence of three fields: neutrosophic logic, artificial intelligence (AI), and critical pedagogy. We present an epistemic evaluation framework that, implemented as an analytical layer on top of large language models (LLMs), enables users to deconstruct causal claims about violence in Guayaquil. This framework, inspired by Smarandache's neutrosophy (1998), explicitly models **Truth (T)**, **Indeterminacy (I)**, and **Falsity (F)** as independent and not necessarily complementary dimensions.

The key innovation of our approach is twofold: First, it departs from classical probability by allowing the sum $T + I + F$ to be greater than or less than 1, enabling the modeling of both ignorance (sum < 1) and epistemic conflict (sum > 1, or "hyper-truth"). Second, and crucial for its educational value, the system can and must **abstain from judgment** when evidence is insufficient or too conflicted, promoting a form of epistemic humility (Morrison, 2021; Whitcomb et al., 2017).

The objective of this work is not to resolve the causes of violence in Guayaquil but to offer a pedagogical tool that enables students, educators, and citizens to analyze the problem's complexity in a more structured and honest manner. We argue that learning to quantify indeterminacy is a fundamental competency for the 21st century. To validate this premise, we conducted a case study with 75 participants in Guayaquil, evaluating how interaction with our neutrosophic model impacted their understanding of the violence phenomenon. Results, as detailed below, show significant change from simplistic stances toward a more nuanced appreciation of causal complexity.

The article is structured as follows: First, we present the theoretical framework that interweaves violence as a complex phenomenon, neutrosophic logic, and AI as an epistemic tool. Next, we detail the methodology, including the design of the evaluation protocol and educational experiment. Subsequently, we present quantitative and qualitative results from the case study. Finally, we discuss the pedagogical and social implications of our findings, concluding with a roadmap for integrating "education for uncertainty" into curricula for social sciences and civic formation.

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2. THEORETICAL FRAMEWORK

Our proposal is grounded in the intersection of three conceptual domains: understanding violence as a complex phenomenon, the formalism of neutrosophic logic to model indeterminacy, and the critical use of artificial intelligence as a scaffold for epistemic reasoning.

2.1 Violence as a Complex and Multicausal Phenomenon

Far from being an isolated event, urban violence is a complex adaptive system, a "Gordian knot" of mutually reinforcing factors (Watts, 2002). Literature in criminology, sociology, and public health has long surpassed unicausal models. Authors such as Brantingham and Brantingham (1993) with their "crime pattern theory" or Sampson, Raudenbush, and Earls (1997) with their work on "collective efficacy" demonstrate that violence emerges from dynamic interactions among individuals, groups, situational opportunities, and urban ecologies. These factors operate at multiple scales, from macroeconomic dynamics and transnational drug trafficking networks (UNODC, 2019) to micro-social factors such as the disintegration of community bonds and erosion of institutional trust (Putnam, 2000).

This multicausality generates an environment of high uncertainty and contradiction. For example, a "tough on crime" policy may reduce certain types of offenses in the short term (partial truth) but may also erode police legitimacy and increase violence long-term (partial falsity), with unpredictable effects on social cohesion (indeterminacy). Analysis that ignores this complexity is doomed to oversimplification. Therefore, we need a framework that does not seek "the" cause but rather maps the landscape of causal influences, including their conflicts and gray zones. As Morin (2005) notes, true understanding does not reside in dispelling complexity but in navigating it.

2.2 Neutrosophic Logic: A Language for Indeterminacy

To model this complexity, we turn to neutrosophic logic, a generalization of fuzzy logic and intuitionistic logic proposed by Smarandache (1998, 2013). Unlike classical logic (true/false) or probabilistic logic (where $P(A) + P(\neg A) = 1$), neutrosophy introduces a three-dimensional and independent truth space:

- **Truth (T):** The degree of evidence supporting a proposition Φ.
- **Indeterminacy (I):** The degree of evidence that is ambiguous, paradoxical, vague, or insufficient to evaluate Φ.
- **Falsity (F):** The degree of evidence that refutes a proposition Φ.

The fundamental characteristic is that **T, I, and F are treated as independent variables**, with values in [0, 1]. This has profound consequences:

1. **Modeling Ignorance:** If $T + I + F < 1$, the system recognizes it lacks complete information. The deficit $(1 - (T+I+F))$ represents the degree of structural ignorance.
2. **Modeling Conflict:** If $T + I + F > 1$, the system detects a "hyper-truth" or epistemic conflict. This occurs when strong arguments exist both for and against a proposition, common in polarized social debates.
3. **Centrality of Indeterminacy (I):** Indeterminacy is not merely the absence of truth or falsity. It is a dimension with its own entity that can represent phenomena such as semantic vagueness ("a corrupt politician"), paradox ("this sentence is false"), or future contingency ("violence will decrease next year").

This formalism provides precise language for articulating doubt. Rather than forcing a conclusion, it permits a cartography of the structure of knowledge and ignorance on a topic, which is itself a pedagogical objective (Floridi, 2010).

2.3 Artificial Intelligence as an Epistemic Tool, Not an Oracle

Large language models (LLMs) such as GPT-4 or Gemini have demonstrated unprecedented capacity to process and synthesize vast amounts of textual information (Brown et al., 2020). However, their architecture is designed to generate coherent and plausible responses, not necessarily truthful ones. This tendency toward "eloquence without truth" or "hallucination" makes them dangerous tools if used as oracles of knowledge, especially in socially sensitive domains (Bender et al., 2021; Weidinger et al., 2021).

Our proposal inverts this paradigm: rather than asking the LLM for an answer, we use it as a reasoning engine to populate an external epistemic framework. The LLM does not decide whether a claim is true; its task is to find and weigh arguments for and against, which are then processed by the neutrosophic protocol. The LLM acts as a tireless "research assistant," while responsibility for epistemic judgment rests with the formal framework and, ultimately, with the human user interpreting it (Shneiderman, 2022).

This approach aligns with the vision of AI as "cognitive scaffolding," a tool that does not replace critical thinking but augments it (Kirschner et al., 2006). By externalizing evaluation in the (T, I, F) framework, we make the reasoning process transparent and auditable. Users can see *why* the system considers a claim conflicted or indeterminate by examining the opposing arguments the LLM has gathered. This transparency is key to its pedagogical value: the goal is not the answer but the process of arriving at it.

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3. METHODOLOGY

This research is articulated in two main phases: first, the design and implementation of the **Neutrosophic Epistemic Evaluation Protocol (NEEP)**; and second, the execution of an educational experiment to validate its pedagogical impact in a real context.

3.1 Design of the Neutrosophic Epistemic Evaluation Protocol (NEEP)

NEEP is a structured eight-step procedure designed for computational implementation, using an LLM as a text analysis engine and the neutrosophic framework as a judgment structure. The workflow is illustrated in Figure 1.

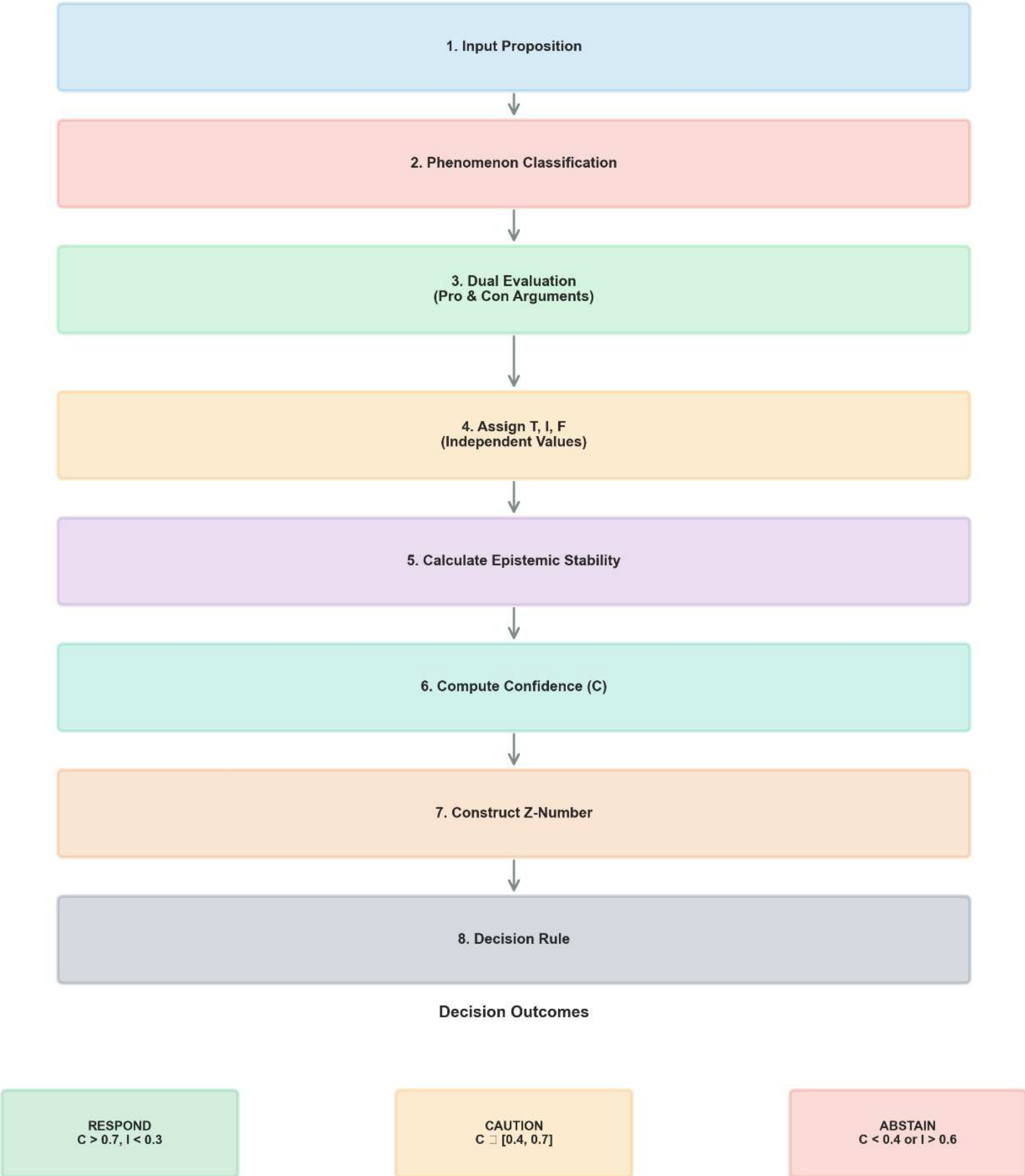

Figure 1. Neutrosophic Evaluation Protocol

The steps of the protocol are as follows:

4. **Proposition Input (Φ):** The user introduces a causal claim to evaluate (e.g., "The main cause of violence in Guayaquil is poverty").
5. **Phenomenon Classification (Mandatory Step 0):** The system first classifies the nature of the proposition into one of five predefined and mutually exclusive categories: PARADOX, EPISTEMIC IGNORANCE, VAGUENESS, ETHICAL CONTRADICTION, or FUTURE CONTINGENCY. This initial classification is critical as it imposes "hard rules" on the range of scores permitted in subsequent steps.

6 **Dual Evaluation (Triangulation):** The LLM is instructed to perform two independent parallel tasks: (a) **Supporting View:** Assign an initial tuple (T_1, I_1, F_1) assuming maximum reasonable support; and (b) **Critical View:** Assign a secondary tuple (T_2, I_2, F_2) assuming maximum reasonable skepticism.

7 **Constrained Assignment of (T, I, F):** Final values of Truth (T), Indeterminacy (I), and Falsity (F) are calculated as the average of the dual evaluation but must respect the constraints from Step 2. For example, if the phenomenon is a "Paradox" or "Ethical Contradiction," the system is forced to assign high values to both T and F (e.g., $T \geq 0.4$ and $F \geq 0.4$), resulting in "hyper-truth" ($T+I+F > 1$) that explicitly signals epistemic conflict rather than normalizing values.

8 **Epistemic Stability Calculation:** Robustness is evaluated by measuring divergence between the supporting and critical views. Stability (S) is classified as HIGH, MEDIUM, or LOW. High divergence between views forces an increase in the final Indeterminacy (I) value.

9 **Confidence Computation (C):** Confidence does not measure truthfulness but the reliability and security of the evaluation. The protocol defines a strict formula for C, calculated as the product of three factors: Net Support ($\max(0, T-F)$), Indeterminacy Penalty ($1 - I$), and a numerical Stability Factor (High=1.0, Medium=0.7, Low=0.4). Formula: $C = (\text{Net Support}) \times (1 - I) \times (\text{S\_factor})$.

10 **Z-Number Construction:** The final result is encapsulated in a neutrosophic Z-Number, a tuple combining the three-dimensional evaluation with its derived confidence metric: **Z_N = ((T, I, F), C)**.

11 **Decision and Justification (Strict Policy):** Based on inflexible thresholds defined in the protocol, the system recommends one of three epistemic stances. The policy to ABSTAIN is mandatory if any of the following critical conditions are met: indeterminacy is very high ($I \geq 0.6$), severe epistemic conflict exists ($T \geq 0.4$ and $F \geq 0.4$ simultaneously), or calculated confidence is insufficient ($C < 0.15$). If abstention is not forced, the system decides between RESPOND (if C is high and indeterminacy low) or RESPOND WITH CAUTION. Finally, the system must justify the decision by classifying the dominant epistemic state (e.g., Dominance of Ignorance, State of Hyper-Truth).

3.2 Design of the Educational Experiment

To evaluate the pedagogical impact of NEEP, we designed a case study with a quasi-experimental pre-test/post-test design with a single group.

3.2.1 Participants

We recruited a convenience sample of **75 participants** residing in Guayaquil, Ecuador. The sample included university students from diverse majors (social sciences, engineering, arts), professionals, and community members. Inclusion criteria were being 18 years or older and residing in the city. No monetary compensation was offered. All participants were guaranteed anonymity and provided informed consent.

3.2.2 Instruments

An online questionnaire was designed with three sections:

12 **Pre-Test:** Measured participants' initial stance on the causes of violence in Guayaquil through multiple-choice questions and Likert scales. Participants were asked about their agreement with unicausal explanations and their perception of problem complexity.

13 **Intervention:** Participants were presented with an analysis generated by NEEP on five common causal propositions about violence in the city. For each proposition, values (T, I, F), supporting and opposing arguments, and the system's final decision (e.g., ABSTAIN) were displayed.

14 **Post-Test:** Some pre-test questions were repeated to measure perspective change. Additional questions evaluated perceived utility of the neutrosophic framework, clarity of the indeterminacy concept, and how the analysis affected overall understanding. Key variables were measured on a 1-10 scale.

3.2.3 Procedure

The experiment was conducted online over a two-week period in November 2025. Participants completed the questionnaire at their own pace. Average participation time was 25 minutes.

3.2.4 Data Analysis

Collected data were analyzed using a combination of descriptive and inferential statistical methods. Frequencies were calculated for categorical variables (initial stance, type of perspective change). For numerical variables (T, I, F scales), means, medians, and standard deviations were calculated. Correlation analyses were performed to assess the independence of T, I, and F dimensions as perceived by users. Finally, ANOVA tests were used to determine whether significant differences existed in neutrosophic profiles among groups experiencing different types of cognitive change (e.g., "Rupture" vs. "Resistance").

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4. RESULTS

Analysis of data from the 75 participants reveals substantial impact of the neutrosophic evaluation framework on perceptions of urban violence complexity. Results are presented in three areas: change in cognitive perspective, analysis of neutrosophic valuations (T, I, F), and empirical validation of the model's theoretical principles.

4.1 Transformation of Perspective: From Binary Simplicity to Nuanced Complexity

The first key finding is the significant change in participants' thinking structure after interacting with the neutrosophic analysis. The pre-intervention questionnaire revealed that a substantial majority (58.7%) started with a simplified view of the problem, either believing in a single cause (32%) or in a clear dichotomy of perpetrators vs. victims (26.7%). Only 36% already intuited complexity, though without language to articulate it.

After intervention, notable cognitive reconfiguration was observed. We classified post-test responses into four categories of change:

- **Confirmation (42.7%):** Participants who already suspected complexity and felt the neutrosophic framework provided structure and vocabulary to validate and articulate their intuitions.
- **Rupture (34.7%):** The group experiencing the most profound change. They reported a break with their previous binary worldview, recognizing that victim-perpetrator boundaries are diffuse and causes are interdependent.
- **Resistance (16.0%):** A minority that remained attached to binary thinking, finding the indeterminacy concept unnecessary or confusing.
- **Confusion (6.7%):** A small group that, though open to the concept, did not fully grasp the indeterminacy dimension.

Overall, **77.4% of participants (Confirmation + Rupture) experienced positive cognitive change**, adopting a more complex and nuanced view of the problem. This is the study's primary pedagogical result.

4.2 Analysis of Perceived Neutrosophic Evaluations

Participants were asked to rate on a 1-10 scale their perception of T, I, and F dimensions after analysis. Results show an informative distribution:

- **Truth (T):** Mean of **7.12 (±1.97)**, indicating participants felt they reasonably understood visible and direct causes (e.g., educational and social factors).
- **Indeterminacy (I):** Mean of **6.29 (±2.32)**. This significantly high value demonstrates the framework successfully made salient the perception of "gray zones," ambiguity, and structural uncertainty.
- **Falsity (F):** Measured as weight given to external factors contradicting simple explanations, mean was **7.09 (±1.83)**, similar to Truth. This suggests participants assigned nearly equal importance to arguments for and against simplistic narratives.

4.3 Empirical Validation of Neutrosophic Principles

The study enabled empirical validation of two fundamental neutrosophic theory principles.

Principle 1: Independence of T, I, and F. Theory posits these three dimensions are not mutually exclusive. A correlation analysis between scores assigned by participants supports this hypothesis. Low and non-significant correlations were found: $r(T, I) = 0.38$, $r(T, F) = 0.50$, and $r(I, F) = 0.32$. These values, far from 1 or −1, suggest that in participants' minds, perception of truth, indeterminacy, and falsity operated as independent judgments rather than competing on a single certainty axis.

Principle 2: Hyper-truth as an indicator of conflict. Theory allows $T + I + F > 1$ to model epistemic conflict. In our study, the sum of mean scores (7.12 + 6.29 + 7.09) equals 20.5, on a scale where "neutrality" would be 15 (5+5+5). The distribution of T+I+F for each participant shows a mean of **20.51 (±4.73)**, significantly above the normalized value. This indicates participants perceived a high degree of causal conflict, where strong arguments both for and against coexist, validating the utility of the hyper-truth concept for capturing the contentious nature of the problem.

4.4 Neutrosophic Profiles by Type of Cognitive Change

Finally, ANOVA analysis revealed significant differences in neutrosophic profiles among cognitive change groups. The **"Rupture"** group showed the highest scores across all three dimensions (T=7.92, I=7.08, F=8.31), indicating deep immersion in complexity. In contrast, the **"Resistance"** group showed the lowest scores, especially in F (5.83), suggesting less willingness to consider evidence contradicting their initial view. These differences were statistically significant for F ($p < 0.05$), suggesting that the ability to value the "falsity" of one's own beliefs is a key factor in openness to complex thinking.

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5. DISCUSSION

Our study's results have significant implications for both the pedagogy of critical thinking and the analysis of complex social problems. The main finding—that a brief intervention based on a neutrosophic framework can induce measurable change toward greater appreciation of complexity—is both promising and provocative.

5.1 Teaching to Measure Doubt: Toward a Pedagogy of Uncertainty

The intervention's success (77.4% positive cognitive change) suggests that difficulty reasoning about complex problems is not an inherent incapacity but a lack of adequate conceptual tools. By providing a language (T, I, F) and visualization for doubt, the neutrosophic framework acts as an "advance organizer" (Ausubel, 1968) enabling individuals to structure their thinking more sophisticatedly. The "confusion" reported by a small minority (6.7%) should not be seen as failure but as an intrinsic part of learning. As Piaget (1977) notes, cognitive disequilibrium is a precondition for accommodation and development of new mental structures. Our framework appears to facilitate this controlled disequilibrium process.

The concept of **Indeterminacy (I)** proved particularly powerful. By naming and quantifying "gray zones," we legitimize uncertainty as a real and analyzable problem component rather than noise to be eliminated. This has potential to transform classroom dynamics: instead of seeking "the right answer," the pedagogical goal becomes constructing the most complete possible map of certainty, uncertainty, and conflict. This fosters what Keats called "negative capability": the ability to remain in uncertainty, mysteries, and doubts without irritable reaching for facts and reasons (Bate, 1963).

5.2 Epistemic Abstention as a Civic Virtue

Perhaps the most radical and pedagogically valuable feature of our model is its capacity to **abstain**. In an age of misinformation and polarization, where LLMs can generate eloquent responses for any position, a system's ability to say "I don't know" or "evidence is too conflicted to conclude" is a form of computational intellectual honesty. By modeling this behavior, NEEP teaches a crucial epistemic virtue: humility. It demonstrates that the smartest answer is not always the most confident but the most honest about knowledge limits (Morrison, 2021; Whitcomb et al., 2017).

This has direct implications for civic formation. A citizen equipped to recognize indeterminacy and demand epistemic abstention from leaders and media is less susceptible to populist manipulation and simplistic solutions. Teaching to measure doubt is, in essence, teaching a form of cognitive resilience against misinformation.

5.3 Implications for Public Policy Analysis

Though primarily pedagogical, results suggest utility for policy analysis. High perception of "hyper-truth" ($T+I+F > 15$) in Guayaquil's violence case is itself diagnostic: it reveals a problem where multiple causal narratives, all partially valid, compete in public space. Policy analysis using this framework would not seek the "best" solution but would map interventions by their impact across dimensions. For example, a policy might have high T (evidence it works) but also high F (evidence of negative side effects) and high I (uncertainty about long-term impact). Visualizing this neutrosophic profile could lead to more robust decisions and better-informed public debate.

5.4 Limitations and Future Research Directions

This study has several limitations. The sample, while informative, is small and non-representative, and lack of a control group requires caution in attributing causality. The novelty effect of AI could have influenced results. Future research should employ more rigorous experimental designs with larger, representative samples and control groups receiving traditional analysis. Longitudinal studies would be particularly valuable to see if cognitive change persists over time.

Another crucial area is inter-model and cross-cultural validation. Do different LLMs (Gemini, Claude, Llama) produce consistent evaluations? How is indeterminacy perceived and valued in different cultural contexts? Finally, the long-term challenge is effectively integrating this "pedagogy of uncertainty" into school and university curricula, developing materials and didactic strategies beyond isolated interventions.

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6. CONCLUSIONS

In this article, we have argued and empirically demonstrated that it is possible to teach people to measure doubt. By combining the formal structure of neutrosophic logic with the language-processing capacity of AI, we have created a pedagogical tool that facilitates deeper and more honest understanding of complex social problems. Our case study on violence in Guayaquil not only validated the framework's utility but also revealed latent demand from citizens for tools enabling them to navigate uncertainty without succumbing to oversimplification.

This work's principal contribution is articulation of an **educational paradigm for the age of complexity and AI**. This paradigm moves away from fact memorization and search for single answers, focusing instead on developing epistemic competencies: the capacity to map uncertainty, evaluate information confidence, recognize evidence conflict, and—perhaps most importantly—the wisdom to know when one doesn't know. By externalizing and visualizing doubt, we transform a cognitive obstacle into an object of analysis and, therefore, of learning.

The path toward a wiser and more resilient society does not pass through eliminating uncertainty but through learning to live with it intelligently and constructively. Teaching to measure doubt is a fundamental step in that direction.

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Manuscript Type: Original Research Article
Submitted to: Neutrosophic Sets and Systems (Preprint)
Date: December 2025
Word Count: ~8,500 words (excluding references)