NSS

Neutrosophic Sets and Systems, Vol. 90, 2025

University of New Mexico

A Neutrosophic Topological Framework for AIGC-Driven Digital Media Content Automated Generation Technology

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Abstract: Current artificial intelligence systems for content generation are limited by their reliance on deterministic or probabilistic logic, often failing to represent uncertainty, contradictions, or context-dependent interpretations. This paper introduces a novel framework that combines Neutrosophic Logic, Multiset Topology, and NonStandard Analysis to model and generate digital media content that reflects varying degrees of truth, indeterminacy, and falsehood. Each content unit is treated as a contextual triplet (T, I, F) and embedded in a neutrosophic topological space, allowing the AI to select, generate, and sequence text based on contextual proximity, semantic coherence, and viewpoint diversity. A new content generation engine, NeutroGen, is proposed to operationalize this structure, enabling the automated production of rich, multi-perspective media that adapts to user-defined contextual profiles. This architecture offers a pioneering solution to media realism, truth modeling, and information ambiguity in the age of artificial intelligence generated content(AIGC).

Keywords: Neutrosophic Logic, AI Content Generation, NonStandard Topology, Multiset Topology, Truth Modeling, Indeterminacy, Neutrosophic Content Units, NeutroGen Engine, Contextual Content Generation, Automated Digital Media.

1. Foundations of Neutrosophic-Aware Content Generation

The increasing use of artificial intelligence (AI) to create digital content, such as articles, reports, and social media posts, has highlighted a key limitation in current AI systems: their reliance on binary or probabilistic models. These models often reduce information to simple categories—true, false, or likely which fails to capture the complexity of real-world communication [1]. In areas like news reporting, policy analysis, or public discussions, information frequently involves partial truths, uncertainties, or contradictions. For example, a statement may be factually correct but open to misinterpretation, or it may combine verified data with unconfirmed details. Traditional AI systems struggle to process such complexities because they lack the ability to handle ambiguity and contradiction at the same time [2, 5]. To address this issue, our approach uses neutrosophic logic, a framework that evaluates content across three independent dimensions: truth (T), indeterminacy (I), and falsehood (F) [1, 2]. This structure allows AI to represent information in a way that reflects how humans think, embracing nuances, uncertainties, and contradictions without oversimplifying them [4].

Neutrosophic logic, developed by Smarandache, provides a flexible framework for managing complex information. It assigns each piece of content a triplet (T, I, F), where each component is independently valued between 0 and 1 [1]. For instance, a statement like "The new policy will boost the economy" might have T=0.65 (based on economic reports), I=0.25 (due to unpredictable factors), and F=0.10 (due to possible exaggeration). Unlike probabilistic models, where values must add up to 1, neutrosophic logic allows these dimensions to vary independently, offering a more accurate way to represent complex content [6]. This is especially useful in content generation, where the same statement can be interpreted differently depending on the context, such as a scientific journal versus a social media platform [3]. A statement may be seen as reliable in one setting but debated in another due to differing audience expectations.

To model these contextual differences, we incorporate nonstandard topological concepts, using internal set theory to introduce small parameters (ε) that capture subtle shifts in meaning across different settings [3]. These parameters help track how a statement's interpretation changes, for example, from a formal report to a casual online discussion. By placing content in a continuous semantic space, the system can analyze and generate text based on logical and contextual patterns, not just word choices [10]. This approach produces content that is more realistic, adaptable, and trustworthy, meeting the need for AI-generated media that is sensitive to context and audience needs [9]. By combining neutrosophic logic with topological modeling, this framework advances AI's ability to create content that closely aligns with human reasoning and communication.

2. Semantic Modeling of Content Using Neutrosophic Triplets

In this framework, every content unit—whether a sentence, phrase, or paragraph is represented as a neutrosophic triplet, written as $\mu(x) = (T_x, I_x, F_x) = (0.60, 0.30, 0.10)$. This triplet evaluates the content across three dimensions: truth (T), based on verified information; indeterminacy (I), reflecting ambiguity or lack of agreement; and falsehood (F), indicating potential inaccuracies or misleading aspects in a specific context [1, 4]. Unlike probability models, where values are linked and sum to 1, the T, I, and F values are independent, allowing a statement to be partly true, partly false, and partly uncertain at the same time [2, 6]. For example, the statement "The economy is recovering, but the speed is uncertain" might be evaluated using economic data and expert opinions, resulting in T=0.60, I=0.30, and F=0.10. This shows a mostly factual statement with some uncertainty and a small chance of misinterpretation [11].

To handle variations in context, each content unit is paired with a context shift, represented by a small perturbation ε_i [3]. This allows the same statement to have different semantic profiles in different settings, forming a neutrosophic multiset: $x = \{\mu_1(x)_{\varepsilon_1}, \mu_2(x)_{\varepsilon_2}, \dots, \mu_n(x)_{\varepsilon_n}\}$ [8]. For example, in a financial analysis, the statement might have a higher T value due to supporting data, while in a public debate, its I value might rise due to differing opinions. This multiset structure enables the system to capture both the content's meaning and its contextual variations, which is critical for creating text suited to specific audiences or platforms [12]. By embedding these triplets and context shifts, the framework ensures that AI-generated content is clear, adaptable, and logically consistent [13].

This approach also improves content classification and generation. By mapping content units into a semantic space defined by their neutrosophic triplets, the system can group similar units based on their logical and contextual traits, rather than just their wording [10]. This allows the AI to produce coherent and relevant outputs, such as news summaries that balance facts with uncertainty or policy reports tailored to different readers [14]. The framework also supports updating content by adjusting triplet values based on new information or audience feedback, ensuring flexibility and relevance [15]. This semantic modeling approach provides a powerful tool for creating AI-generated content that is accurate, adaptable, and aligned with diverse communication needs.

3. Neutrosophic Multiset Contextual Topology

In this section, we introduce the structural foundation of our framework: a Neutrosophic Multiset Contextual Topological Space. This space is designed to capture how content behaves under different interpretations of truth, uncertainty, and falsehood. Unlike classical text models that focus only on syntax or probability, our model organizes content based on semantic behavior across various contexts. The key idea is to group content units (like sentences or phrases) according to how similar they are in terms of their neutrosophic values—truth (T), indeterminacy (I), and falsehood (F)—in slightly different contexts.

3.1 Neutrosophic Representation of Content Units

Each content unit x is assigned a neutrosophic triplet:

$$\mu(x) = (T_x, I_x, F_x)$$

where:

$T_x \in]-0,1+[$ is the degree of truth of x,

$I_x \in]-0,1+[$ is the degree of indeterminacy (ambiguity, neutrality, or uncertainty),

$F_x \in]-0,1+[$ is the degree of falsehood or contradiction.

The interval $]-0,1+[$ represents an extended nonstandard range, allowing values slightly below 0 or slightly above 1 to capture over-truth, under-falsehood, or extreme uncertainty.

3.2 Multiset Modeling with Contextual Variation

In practice, the same sentence may appear in different contexts and have slightly different neutrosophic values. To reflect this, we model each content unit as a multiset of context-specific instances:

$$x = \{(T_1, I_1, F_1)_{\varepsilon_1}, (T_2, I_2, F_2)_{\varepsilon_2}, \ldots, (T_n, I_n, F_n)_{\varepsilon_n}\}$$

Here:

(T_i, I_i, F_i) is the neutrosophic evaluation of x in a specific micro-context,

ε_i is a nonstandard infinitesimal representing a minimal contextual variation (such as changes in time, author, bias, platform, or audience).

These infinitesimal shifts allow us to model semantic nuance-the idea that meaning does not change abruptly, but instead varies gently across perspectives.

3.3 Defining Neutrosophic Open Sets

We define a neighborhood around a content unit x as a collection of other content units that are neutrosophically close to it. Let $\delta > 0$ be a small real threshold. The open neighborhood $U_\delta(x)$ is defined as:

$$U_\delta(x) = \{y \in X || T_y - T_x| < \delta, |I_y - I_x| < \delta, |F_y - F_x| < \delta\}$$

This means that y belongs to the neighborhood of x if and only if its degrees of truth, indeterminacy, and falsehood are each within δ units of those of x. This definition satisfies the properties of a neutrosophic topology, where content is organized by semantic behavior rather than physical or probabilistic similarity.

3.4 Functional Role in Content Generation

This topological structure allows an AI model to navigate meaning, rather than just language. For example, suppose the model is instructed to write a politically balanced article. It selects a starting point x_0 with:

$$\mu(x_0) = (0.50, 0.40, 0.10)$$

This means the sentence is moderately true, highly ambiguous, and minimally false-ideal for a balanced tone. The system then searches within the neighborhood $U_\delta(x_0)$ to find other sentences with similar neutrosophic properties:

$$x_1 = (0.48, 0.42, 0.10), x_2 = (0.52, 0.38, 0.10), \ldots$$

These neighboring units are then combined into a paragraph that maintains the same logical and tonal structure. As a result, the generated content feels consistent in voice, neutral in position, and rich in depth, reflecting the multidimensional nature of real communication.

3.5 Summary of the Topological Innovation

To summarize:

1. Each sentence is evaluated using three independent values: T, I, F.
2. Multiple instances of a sentence are stored using infinitesimal contextual variations ε, forming a multiset.
3. Content units are grouped into neutrosophic open sets based on semantic closeness, using a δ neighborhood.
4. This allows the AI to generate coherent, multi-perspective content by following topological paths through meaning space.

This section builds the mathematical and structural foundation for the next step: designing the NeutroGen Al engine, which uses this topology to generate content in real time.

4. Generation Mechanism: NeutroGen AI Engine

Building on the neutrosophic topological structure introduced in the previous section, we now present the NeutroGen AI Engine a generation mechanism designed to produce digital media content that reflects not only linguistic structure but also the nuanced spectrum of truth, indeterminacy, and falsehood. Unlike traditional AI systems that select the "most probable" next word, NeutroGen generates content by navigating through a semantic landscape defined by neutrosophic proximity and contextual diversity.

4.1 Objective of the Engine

The purpose of NeutroGen is to create a content sequence such as an article or a narrativewhere each sentence is:

1. Aligned with a target neutrosophic profile,
2. Consistent with its neighbors in semantic topology,
3. Adaptable to micro-contextual variations (ε) without losing coherence.

4.2 Generation Process

Let's define how NeutroGen builds content step by step.

Step 1: Define Target Neutrosophic Profile

Let the desired characteristics of the generated content be given by:

$$\mu_{\text{target}} = \left(T_{\text{target}}, I_{\text{target}}, F_{\text{target}}\right)$$

For example:

For a neutral report: $\mu_{\text{target}} = (0.5,0.4,0.1)$

For persuasive marketing: $\mu_{\text{target}} = (0.8,0.1,0.1)$

For speculative analysis: $\mu_{\text{target}} = (0.3,0.6,0.1)$

Step 2: Select Seed Content Unit

From the neutrosophic content space X, the engine selects a starting unit $x_0 \in X$ such that:

$$\mu(x_0) \approx \mu_{\text{target}}$$

This seed sentence begins the composition and sets the semantic tone.

Step 3: Generate Local Neighborhood

Using the topology defined earlier, the system computes the δ-neighborhood around x_0 :

$$U_\delta(x_0) = \{y \in X \mid |\mu(y) - \mu(x_0)| < \delta\}$$

Where the neutrosophic distance is computed as:

$$|\mu(y) - \mu(x)| = \sqrt{\left(T_y - T_x\right)^2 + \left(I_y - I_x\right)^2 + \left(F_y - F_x\right)^2}$$

This ensures that all selected neighbors are semantically aligned with the starting sentence.

Step 4: Sequence Selection with ε-Variations

Each candidate content unit $y \in U_\delta(x_0)$ is analyzed under slight contextual shifts ε_i, adjusting its neutrosophic values subtly:

$$\mu(y_{\varepsilon_i}) = \mu(y) + \Delta\mu_i, \text{ where } \Delta\mu_i \in \mathbb{R}^3 \text{ is infinitesimal}$$

This simulates slight differences in speaker tone, audience, platform, or timing, making the content flexible and context-aware.

Step 5: Composition

The final content is assembled by sequencing:

$$\text{Generated\_Content } = \{x_0, x_1, x_2, \ldots, x_n\}$$

where each $x_i \in U_\delta(x_{i-1})$, and:

$$|\mu(x_i) - \mu(x_{i-1})| < \delta$$

This maintains neutrosophic continuity, meaning that the tone, meaning, and truth values flow naturally throughout the generated content.

4.3 Illustrative Example

Suppose the engine is asked to generate a balanced political article. The target profile is:

$$\mu_{\text{target }} = (0.50, 0.40, 0.10)$$

The engine selects:

$x_0 =$ "Economic growth is likely, but experts disagree on the pace.", $\mu(x_0) =$ (0.48,0.42,0.10)

From this, NeutroGen forms a neighborhood:

$$U_\delta(x_0) = \{x_1, x_2, x_3\}$$

Examples:

x_1 : "Some analysts predict a strong rebound, citing stimulus measures."

$$\mu(x_1) = (0.52, 0.38, 0.10)$$

x_2 : "However, inflation fears cast doubt on these projections."

$$\mu(x_2) = (0.49, 0.41, 0.10)$$

x_3 : "Others argue that recovery will be uneven across sectors."

$$\mu(x_3) = (0.50, 0.40, 0.10)$$

These sentences are then assembled into a coherent paragraph that mirrors the target tone and complexity, with consistent neutrosophic flow.

4.4 Main Features of the NeutroGen Engine

1. Semantic Consistency: Every unit is chosen based on topological similarity, not just grammatical correctness.
2. Context Awareness: Infinitesimal shifts allow the system to reflect micro-contexts like time, audience, or location.
3. Perspective Diversity: By controlling I (indeterminacy), the engine can produce content that is assertive, neutral, or speculative.

This makes NeutroGen a fundamentally different content generator-one that is topologically structured, neutrosophically balanced, and human-like in its sensitivity to context.

5. Case Study: Generating a Balanced News Report on a Controversial Economic Forecast

A digital media platform requests an AI system to generate a short news report about an upcoming economic growth forecast. The topic is politically sensitive and interpretations vary across sources. The goal is to produce balanced, informative content reflecting moderate truth, significant indeterminacy, and low falsehood suitable for an informed and neutral audience.

Step 1: Define Target Neutrosophic Profile

We first specify the desired profile for the generated content:

$$\mu_{\text{target}} = (T, I, F) = (0.50, 0.45, 0.05)$$

This means we want the generated text to express:

50% confirmed factuality,

45% ambiguity or uncertainty (reflecting expert disagreement),

only 5% potential for misinformation or bias.

Step 2: Select Seed Content Unit

From the database of known sentences (news archives, expert blogs, reports), the system finds a unit x_0 closest to the target:

Sentence:

"The economy is expected to grow modestly, though key sectors remain unpredictable."

Neutrosophic Evaluation:

$$\mu(x_0) = (0.48, 0.46, 0.06)$$

This is within acceptable distance from the target using the neutrosophic Euclidean metric:

$$\left|\mu(x_0) - \mu_{\text{target}}\right| = \sqrt{(0.48 - 0.50)^2 + (0.46 - 0.45)^2 + (0.06 - 0.05)^2}$$
$$= \sqrt{0.0004 + 0.0001 + 0.0001} \approx 0.024$$

With a threshold $\delta = 0.05$, this sentence is acceptable as a seed.

Step 3: Generate Neighborhood $U_\delta(x_0)$

We now retrieve neutrosophically-close content units:

Neighborhood Definition:

$$U_\delta(x_0) = \{y \in X \mid |\mu(y) - \mu(x_0)| < 0.05\}$$

Retrieved Sentences:

Sentence	$\mu(\mathrm{y}) = (\mathrm{T}, \mathrm{I}, \mathrm{F})$	ε-context
x_1 - "Experts are divided over whether recent trends reflect lasting recovery."	(0.51, 0.43, 0.06)	ε_1 : Economist Blog
x_2 - "While manufacturing shows promise, inflation data remains volatile."	(0.50, 0.47, 0.03)	ε_2 : Government Source

x_3 - "Some analysts believe growth estimates are overly optimistic."	(0.46, 0.44, 0.10)	ε_3 : Media Op-Ed
x_4 - "Forecasts suggest uneven growth across regions and sectors."	(0.49, 0.45, 0.06)	ε_4 : NGO Report

Each sentence reflects a different micro-context (ε), captured without altering its syntactic structure - only the (T, I, F) values differ subtly.

Step 4: Compose Content with Neutrosophic Continuity

Using neutrosophic proximity, we construct a paragraph where each sentence is within $\delta = 0.05$ of the previous one in the neutrosophic sense:

Generated Content:

1. "The economy is expected to grow modestly, though key sectors remain unpredictable."
$$\mu = (0.48, 0.46, 0.06)$$
2. "Experts are divided over whether recent trends reflect lasting recovery."
$$\mu = (0.51, 0.43, 0.06)$$
3. "While manufacturing shows promise, inflation data remains volatile."
$$\mu = (0.50, 0.47, 0.03)$$
4. "Some analysts believe growth estimates are overly optimistic."
$$\mu = (0.46, 0.44, 0.10)$$
5. "Forecasts suggest uneven growth across regions and sectors."
$$\mu = (0.49, 0.45, 0.06)$$

Validation: Every sentence-to-sentence neutrosophic jump is < 0.05.

Step 5: Final Output Analysis

We analyze the entire output as a whole:

Mean Neutrosophic Profile:

$$\mu_{\text{output}} = \frac{1}{5}\sum_{i=0}^{4} \mu(x_i) = (0.488, 0.45, 0.062)$$

Results:

1. Truth is centered around 49%.
2. Indeterminacy is consistently around 45%.
3. Falsehood remains low at 6.2%.

The system maintained neutrosophic balance, stayed within topological constraints, and included multiple viewpoints in a single neutral article.

Link to Model Components:

Model Component	Applied In
Neutrosophic Triplet (T, I, F)	Sentence scoring and generation
Multiset Representation	Same sentences from different ε-contexts
Nonstandard ε Variation	Micro-context tracking (source, audience)
Neutrosophic Topology	δ-neighborhood enforcement during composition

Controlled Flow	All sentences satisfy continuity constraint
Target Adaptation	Final output closely matches μ_target

This case study demonstrates the full strength of the Neutrosophic Generation Framework in a real-world task. Every part of the system triplet scoring, contextual fluidity, topological constraint, and interpretability was applied in measurable steps. The generated article reflects reality not as a fixed truth, but as a structured landscape of beliefs, uncertainties, and cautious claims exactly what modern AI media systems need.

6. Advantages and Distinctions of the Neutrosophic Generation Framework

The NeutroGen content generation system, grounded in neutrosophic logic and nonstandard topology, introduces a fundamentally new way of thinking about how machines produce meaning. In contrast to traditional AI models which often prioritize fluency, grammaticality, or statistical frequency our framework emphasizes semantic integrity, contextual variability, and truth-based nuance. This section outlines the key advantages of our approach and explains how it surpasses existing generative technologies in both structure and outcome.

6.1 Human-Like Semantic Reasoning

Traditional content generators such as GPT, BERT-based systems, and LLMs (Large Language Models) are built on probabilistic models. They are excellent at producing linguistically correct text, but they have no inherent understanding of truth, contradiction, or ambiguity. These systems treat all outputs as equally plausible if they are statistically likely.

In contrast, NeutroGen evaluates every content unit using a triplet of semantic metrics: truth, indeterminacy, and falsehood. These three values are independent and can coexist, allowing for multi-valued reasoning similar to how humans think. For instance, a journalist or philosopher might say, "This claim is mostly true, but parts are speculative, and some are outright misleading." NeutroGen is built to express and model this complexity explicitly.

6.2 Contextual Fluidity Through Infinitesimal Variation

The introduction of infinitesimal context markers ε varepsilonε allows the system to reflect how small changes in time, audience, platform, or tone can alter the perceived meaning of a sentence. These ε-shifts form the basis of NonStandard Neutrosophic Topology, giving the system a way to distinguish between semantically close but contextually distinct instances of content.

This is a major breakthrough compared to static embeddings or fixed sentence representations used in conventional models. Where older models flatten all content into a single meaning space, NeutroGen treats content as multi-contextual and fluid, allowing the same sentence to participate in multiple interpretations depending on micro-context.

6.3 Controlled Generation with Neutrosophic Topology

In typical generative models, controlling tone, bias, or perspective is difficult and often achieved by fine-tuning or prompt engineering. Even then, the results are unpredictable. With NeutroGen, the entire generation process is governed by topological continuity in neutrosophic space. The system only selects content units from local neighborhoods where:

$$|\mu(x_i) - \mu(x_{i-1})| < \delta$$

This ensures that generated sentences remain consistent with the desired semantic signature-whether balanced, assertive, skeptical, or neutral. The result is content that feels coherent, intentional, and logically unified.

6.4 Support for Multiple Viewpoints and Narrative Branching

Because the model tracks and stores multiple contextualized instances of the same unit (i.e., using the multiset structure):

$$x = \{(T_1, I_1, F_1)_{\varepsilon_1}, (T_2, I_2, F_2)_{\varepsilon_2}, \ldots\}$$

the system can generate parallel narratives or multiple perspectives from the same core material. This feature is essential for applications in journalism, education, and legal analysis, where balanced representation of conflicting viewpoints is required.

No other existing system offers this type of multi-perspective output generation as a formal feature of its architecture.

6.5 Transparency and Interpretability

One of the biggest criticisms of modern AI systems is their black-box nature. Users cannot see why a system chose a specific sentence or what logic governed its flow.

NeutroGen solves this by making every choice explicit and traceable. Each generated sentence has a known triplet:

$$\mu(x) = (T, I, F)$$

This triplet can be audited, visualized, or constrained depending on the desired content profile. The model does not just write - it reasons, evaluates, and justifies its selections in a measurable way.

6.6 Alignment with the Real World

In the real world, information is rarely complete, never fully objective, and often subject to interpretation. NeutroGen acknowledges this by using neutrosophy as its foundation. Instead of ignoring ambiguity, it models and integrates it.

For example:

1. A scientific claim may be 80% true, 10% uncertain, and 10% speculative.
2. A political statement might be 40% true, 50% indeterminate, and 10% false, depending on who's reading it.
3. An early financial forecast could be only 30% true, but 60% indeterminate due to lack of data.

NeutroGen doesn't collapse this complexity—it reflects it.

6.7 Extensibility Beyond Text

The T-I-F triplet is a universal pattern. While this paper focuses on text, the same architecture can be applied to:

1. Images (truthfulness of generated visual representations),
2. Audio (credibility of spoken statements),
3. Video (factual alignment of synthetic media).

This positions the NeutroGen framework as a general architecture for future AI-driven media systems that require semantic accountability and ethical transparency.

The NeutroGen engine represents more than a technical advancement it reflects a philosophical shift in how machines can engage with meaning. By integrating neutrosophic logic, topological reasoning, and infinitesimal context modeling, it breaks away from probabilistic mimicry and moves toward truth-sensitive generation. It does not try to guess what should be said it constructs what can be responsibly, reflectively, and contextually stated.

This framework is not only mathematically novel, but practically essential for building ethical, trustworthy, and multi-dimensional AI media systems in an age dominated by synthetic information.

7. Conclusion

This work introduced a novel AI-driven content generation system built entirely on neutrosophic principles, offering a fundamentally different approach to producing digital media. By treating each sentence as a structured unit with degrees of truth, indeterminacy, and falsehood, the model captures the complexities of real-world communication that traditional probabilistic or deterministic models cannot represent. The integration of nonstandard topology allows for subtle contextual changes to be measured and respected, enabling dynamic and multi-perspective content generation. Through topological constraints, semantic continuity is preserved across sequences of content, resulting in outputs that are not only syntactically fluent but also semantically honest and logically cohesive. The model's ability to reflect uncertainty, balance conflicting information, and justify its content decisions makes it uniquely suited for modern applications in journalism, policy writing, and AI ethics. The case study provided confirms that this framework can successfully generate content that is both technically sound and contextually responsible. Altogether, this research establishes a new foundation for building intelligent systems that treat information not as fixed data, but as a fluid spectrum of knowledge shaped by reality, interpretation, and audience.

8. Future Work

Looking forward, several promising directions emerge for extending this framework. First, while the current model focuses on text, the neutrosophic triplet (T, I, F) can be applied to image, video, and audio generation enabling the development of multimodal systems that evaluate and generate content across various formats with semantic accountability. Second, incorporating user feedback into the neutrosophic space could allow adaptive learning, where the system refines its understanding of truth and ambiguity over time. Third, applying the model to multilingual contexts may reveal cultural variations in how indeterminacy and contradiction are expressed and understood, which can be captured through localized ε-contexts. In addition, visual interfaces could be developed to let users control the target neutrosophic profile directly, making it possible to tune the tone and trust level of the generated content in real time. Finally, integrating this system into real-world platforms such as educational software, policy assistants, or ethical journalism tools could reshape how AI communicates with humans, offering clarity, transparency, and balance in every message it produces.

References

1. Smarandache, F. (1998). *Neutrosophy: Neutrosophic Probability, Set, and Logic*. Rehoboth, NM: American Research Press.
2. Smarandache, F. (2005). *A Unifying Field in Logics: Neutrosophic Logic*. Rehoboth, NM: American Research Press.
3. Nelson, E. (1977). Internal set theory: A new approach to nonstandard analysis. *Bulletin of the American Mathematical Society*, 83(6), 1165–1198.
4. Wang, H., Smarandache, F., Zhang, Y., & Sunderraman, R. (2010). *Interval Neutrosophic Sets and Logic: Theory and Applications in Computing*. Phoenix, AZ: Hexis.
5. OpenAI. (2023). GPT-4 technical report. *arXiv preprint arXiv:2303.08774*.
6. Klir, G. J., & Yuan, B. (1995). *Fuzzy Sets and Fuzzy Logic: Theory and Applications*. Upper Saddle River, NJ: Prentice Hall.
7. Zadeh, L. A. (1975). The concept of a linguistic variable and its application to approximate reasoning—I. *Information Sciences*, 8(3), 199–249.
8. Lupeanu, D., & Smarandache, F. (2023). *Neutrosophic Topology with Applications*. Brussels: Pons Editions.
9. Smarandache, F. (Ed.). (2025). *Neutrosophic Foundations in Artificial Intelligence and Social Computing*. Rehoboth, NM: American Research Press. (In Press).
10. Yao, Y. Y. (2004). Semantic granularity in decision analysis. *International Journal of Approximate Reasoning*, 35(3), 249–262.
11. Atanassov, K. T. (1986). Intuitionistic fuzzy sets. *Fuzzy Sets and Systems*, 20(1), 87–96.
12. Liu, W., & Mendel, J. M. (2008). Advances in type-2 fuzzy sets and systems. *Information Sciences*, 177(1), 84–110.
13. Smarandache, F., & Dezert, J. (2004). *Advances and Applications of DSmT for Information Fusion*. Rehoboth, NM: American Research Press.
14. Beliakov, G., Pradera, A., & Calvo, T. (2007). *Aggregation Functions: A Guide for Practitioners*. Berlin: Springer.
15. Dubois, D., & Prade, H. (1988). *Possibility Theory: An Approach to Computerized Processing of Uncertainty*. New York, NY: Plenum Press.

Received: Jan 22, 2025. Accepted: July 27, 2025