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A Neutrosophic Approach to Study Agnotology: A Case Study on Climate Change Beliefs

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Abstract

Misinformation and biased information significantly impact public perception and political decisions, especially on critical issues such as climate change and environmental conservation. This study aims to understand how indeterminacy and contradiction influence public perception and policy formulation by applying neutrosophic theory to model the complexity and multi-dimensionality of ignorance. Using neutrosophic Likert scales, we capture a nuanced spectrum of opinions on the scientific certainty of human impact on climate change. The results are analyzed through a k-means clustering algorithm to identify patterns and segment participants into groups based on their levels of truth, indeterminacy, and falsehood. This approach reveals deeper insights into public perceptions and aids in evaluating their implications for effective communication and policy-making.

Keywords: Neutrosophy, Agnotology, Climate Change Perception, Neutrosophic Likert Scales.

1 | Introduction

Misinformation and biased information have a significant impact on public perception and political decisions, especially on critical issues such as climate change and environmental conservation. This study aims to better understand how indeterminacy and contradiction influence public perception and policy formulation, applying neutrosophic theory to model the complexity and multi-dimensionality of ignorance. Agnotology [1] helps to understand how knowledge and ignorance are not simply opposites, but that ignorance can be manufactured and maintained through specific strategies, affecting public perception and political decisions.

The rise of generative artificial intelligence has revolutionized the creation and dissemination of disinformation, exacerbating phenomena already studied such as agnotology (the study of disinformation), agnoiology (the study of ignorance), aningmology (the study of creating doubt), and cognitronics (the study of perception distortion). The ability of these technologies to generate convincing content at scale has increased the efficiency and reach of disinformation, posing new challenges in the fight for truth and the integrity of knowledge in the digital age [2].

Neutrosophy, a philosophy developed by the Romanian scientist Florentin Smarandache, provides a theoretical framework that addresses the coexistence and interactions between elements of truth, falsehood, and neutrality [3]. In exploring agnotology through a neutrosophic lens, this study harnesses the mathematical formalisms associated with the social structures of truth (T), uncertainty (I), and falsehood (F) to examine the

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deliberate production of ignorance. By adopting a neutrosophic approach, we move beyond the binary framework of true or false to incorporate the crucial aspect of uncertainty, providing a more comprehensive understanding of knowledge dynamics. This framework facilitates the interrogation of how different societal beliefs and perceptions contribute to the systematic obscuration or distortion of information.

Utilizing neutrosophic Likert scales [4] in our survey design allows for a nuanced capture and analysis of these T, I, and F structures, offering a robust methodological tool to assess their prevalence and influence on public discourse and policy. This approach not only aids in pinpointing areas of informational conflict and consensus but also highlights zones of indeterminacy that are critical for a deeper understanding of agnotological processes. In this paper, we explore public perceptions regarding the impact of human activities on Earth's climate, an area where there is great scientific consensus [5] but where ignorance persists or has been deliberately created [6].

2 | Preliminaries

2.1 | Neutrosophic Set

Neutrosophic sets [7] offer a method for analyzing questionnaire responses, surpassing the capabilities of traditional fuzzy sets or intuitionistic sets by incorporating a unique indeterminacy function [8]. This function captures not only the degrees of truth and falsehood but also the critical dimension of indeterminacy. This additional layer allows for a more comprehensive representation of human responses, particularly useful in scenarios where answers may contain elements of contradiction, ambiguity, or uncertainty. Neutrosophic sets enable respondents to communicate their true thoughts and emotions with greater precision, capturing a broader spectrum of human cognition and perception.

By employing neutrosophic sets in survey analysis [8], researchers can achieve a deeper and more accurate understanding of respondent attitudes and behaviors. The inclusion of indeterminacy helps reveal the complexities and nuances in responses that traditional methods might overlook. This approach enriches data interpretation and enhances decision-making processes by providing a clearer insight into the diverse perspectives and uncertainties that characterize human responses, making neutrosophic sets a superior tool for capturing the full range of possible answers in questionnaires [9]. Next, we present basic definitions and concepts concerning neutrosophic sets and single-valued neutrosophic sets.

Definition 1 [10]: Let U be a discourse universe. $N=\{(x, T(x), I(x), F(x)) : x \in U\}$ is a neutrosophic set, denoted by a truth-membership function, $TN : U \rightarrow]0-, 1+[$; an indeterminacy-membership function, $IN : U \rightarrow]0-, 1+[$; and a falsity-membership function, $FN : U \rightarrow]0-, 1+[$.

Single-valued neutrosophic sets provide a way to represent and analyze possible elements in the discourse universe U.

Definition 2 [11]: Let U be a discourse universe. A single-valued neutrosophic set is defined as $N=\{(x, T(x), I(x), F(x)) : x \in U\}$, which is identified by a truth-membership function, $TN : U \rightarrow [0, 1]$; indeterminacy-membership function, $IN : U \rightarrow [0, 1]$; and falsity-membership function, $FN : U \rightarrow [0, 1]$, with $0 \le TN(x)+IN(x)+FN(x) \le 3$.

Neutrosophic logic [12] is an emerging field in which each proposition is considered to have proportions of truth, indeterminacy, and falsehood. This ability to handle multiple and varied degrees of truth and falsehood is particularly useful in contexts where information is paradoxical, inconsistent, or incomplete.

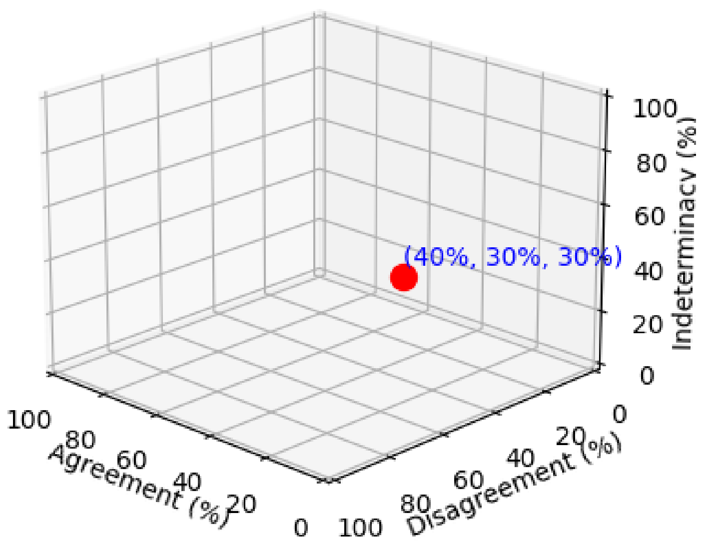

Figure 1. Neutrosophic representation space.

2.2 | Neutrosophic Likert Scales

In the study of Agnotology, social structures, identified through the categories of truth (T), uncertainty (I), and falsehood (F), can be captured and analyzed effectively through survey analysis [13eutrosophic sets, and consequently neutrosophic Likert scales, offer an expanded framework that includes indeterminacy as a fundamental element. In contrast, fuzzy sets facilitate the depiction and handling of data that lack precise specification. For survey responses in which participants' opinions not only vary across a spectrum (as accommodated by fuzzy sets) but also may include a degree of indecision or neutrality that is difficult to capture using traditional fuzzy logic or crisp Likert scales, neutrosophic Likert scales are, therefore, particularly well suited [14, 15].

The score function grounded in neutrosophic theory, effectively transforms responses from neutrosophic Likert scales into a consolidated single value.

Definition 3 [13]: Let A = (T, I, F) be a single-valued neutrosophic number. A score function S for this single-valued neutrosophic number, which is derived from the truth-membership degree, indeterminacy-membership degree, and falsity-membership degree, is defined as follows:

$$S(A) = \frac{1 + a - 2b - c}{2} \tag{1}$$

where S(A) ∈ [−1,1].

Surveys utilizing neutrosophic Likert scales effectively measure the diversity of opinions and their influence on public policy and social discourse, capturing areas of consensus, disagreement, and ambivalence. Neutrosophic logic, critical in Agnotology, analyzes the coexistence of different "truths" and the spectrum of "falsehoods," revealing how knowledge is shaped and sometimes obscured within cultural and social frameworks.

3 | Material and Methods

The survey was conducted with 25 university students at the University of Guayaquil in Ecuador. The primary question posed to participants was: "Based on your understanding, how scientifically certain is it that human activities are affecting Earth's climate?" The responses were structured on a neutrosophic Likert scale, allowing participants to express options that align with the neutrosophic framework.

- "Very sure (the scientific evidence is robust and widely accepted)", which corresponds to a high truth value (T).
- "Indeterminate (there are studies supporting it, but the consensus is unclear)", which captures the state of uncertainty (I).
- "Not sure (the scientific evidence is not convincing)", which is associated with falsehood (F).

Answers are classified according to the sum of the True, Indeterminate, and False components as follows:

- T+I+F<1: Incomplete
- T+I+F=1: Complete
- T+I+F>1: Contradictory

The k-means clustering analysis was performed on the dataset composed of the triplets (T, I, F) from each response. The objective was to identify patterns and segment the participants into homogeneous groups based on their levels of scientific certainty about human impact on climate change [16].

To perform the clustering, the following steps were followed:

i. Initialization: A number k of clusters was selected. In this case, $k = 3$ was chosen to identify three distinct groups of responses based on the Elbow Method [17] for the optimal value of k.

ii. Cluster Assignment: Each response (T, I, F) was assigned to the cluster whose centroid (mean of the points within the cluster) was nearest, by calculating the Euclidean distance. Given n responses (T_i, I_i, F_i) for i=1,2,…,n, i=1,2,…,n and a number of clusters k, the algorithm aims to minimize the sum of squared distances between each point and its corresponding centroid:

$$\min \sum_{j=1}^{k} \sum_{i \in C_j} \| (T_i, I_i, F_i) - \mu_j \|^2 \quad (2)$$

where C_j is the set of points assigned to cluster j and $\mu_j$is the centroid of cluster j.

iii. **Centroid Update:** The centroids of each cluster were recalculated based on the responses assigned to each one.

iv. **Iteration:** Steps 2 and 3 were repeated until the cluster assignments did not significantly change between iterations.

The scoring function (1) presented in this study effectively balances the influence of truth, indeterminacy, and falsehood, providing a nuanced view of the respondents' perceptions. To measure agreement with scientific certainty, the function assigns a greater negative weight to uncertainty. This approach permits a more complete and improved analysis of the data, capturing a detailed picture of respondents' levels of agreement.

4 | Results

Most of the responses (17 out of 24) fall into the "Contradictory" category as shown in Figure 2, suggesting that respondents perceive a higher level of complexity and inconsistency in the scientific certainty regarding human impact on climate change.

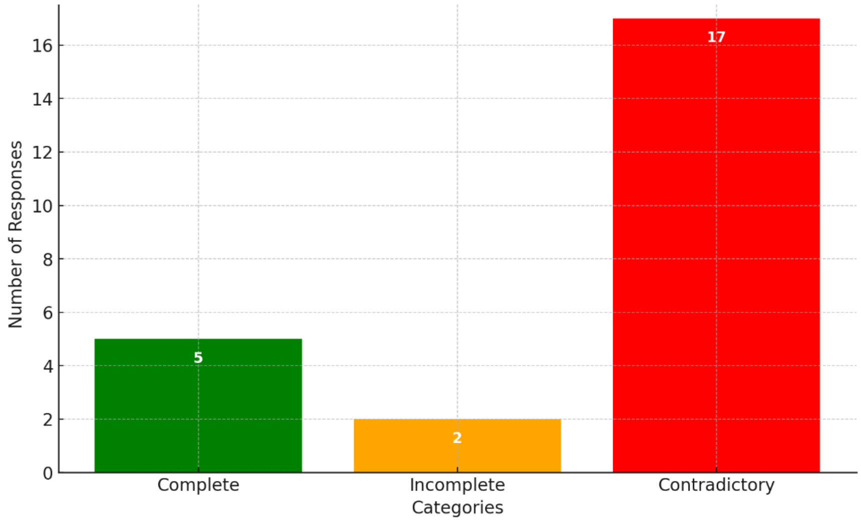

Figure 2. Neutrosophic classification of responses on scientific certainty about human impact on climate change.

This finding highlights the prevalence of conflicting beliefs and uncertainty among the public. The presence of more "Contradictory" responses suggests that people recognize the multifaceted nature of scientific evidence and the difficulty in reaching a definitive conclusion. This underscores the importance of addressing gaps in knowledge and understanding the reasons behind contradictory viewpoints to foster better communication and education on climate science.

The analysis utilized a k-means clustering algorithm to categorize the responses into three distinct clusters based on the variables Truth (T), Indeterminacy (I), and Falsehood (F) as presented in Figure 3. This approach aimed to uncover patterns in respondents' perceptions regarding the scientific certainty of human impact on climate change.

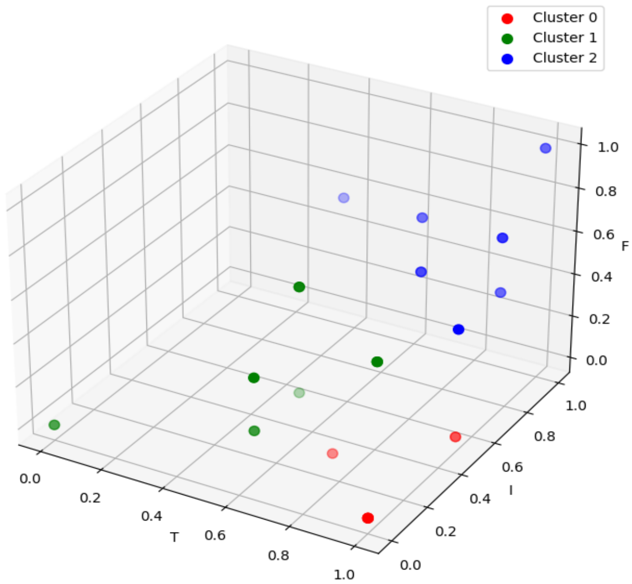

Figure 3. Distribution of clusters in three-dimensional space for variables T, I, and F.

In the context of the clusters derived from the data, the following interpretations can be made:

- Cluster 0 (Red): This cluster represents individuals who have higher values of certainty (T) but lower values in indeterminate (I) and false (F). This suggests that these people have a firmer and more certain understanding of human influence on climate change, with fewer doubts or contradictory beliefs.

- Cluster 1 (Green): This cluster is characterized by varied but generally lower values in certainty (T) and greater dispersion in indeterminate (I) and false (F). This might indicate individuals who have greater uncertainty and contradictory beliefs about human influence on climate change, reflecting a less firm understanding and more doubts.
- Cluster 2 (Blue): This cluster includes individuals with a wide variety of values, with some having high certainty (T) and others having higher values in indeterminate (I) and false (F). This may indicate a mix of undecided or skeptical people regarding the scientific certainty of human activities affecting the climate, showing the complexity and multifaceted nature of ignorance and uncertainty.

The graph of the survey responses, as shown in Figure 4, illustrates the distribution of scores. The scores range from −0.5 to 1.0 with an average score of approximately 0.245. This average indicates a slight overall agreement with the scientific certainty of human impact on climate change. Positive scores suggest a higher confidence in the scientific certainty, while negative scores highlight areas of doubt and disagreement.

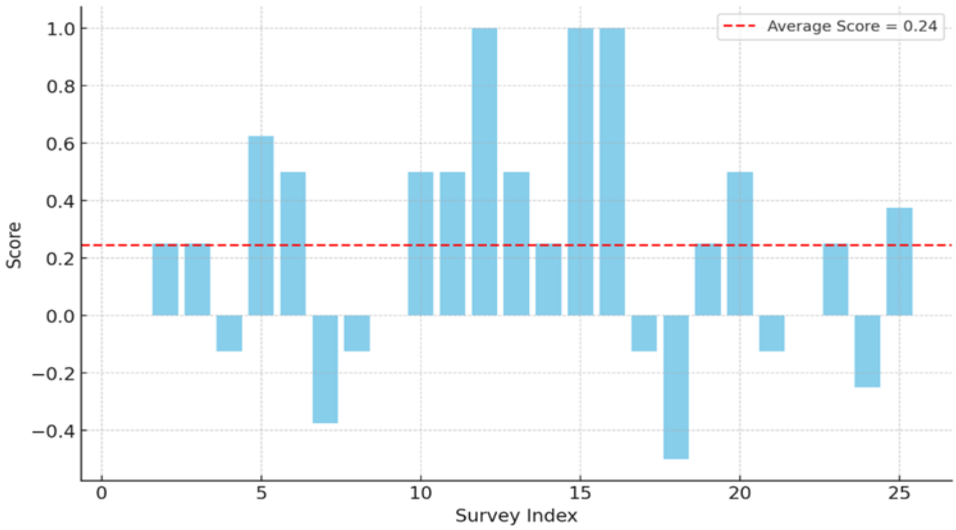

Figure 4. Score function results by survey.

The interpretation of the scores reveals significant insights into public perceptions:

Positive Scores: These scores, which range up to 1.0, indicate respondents who have a higher confidence in the scientific evidence of human impact on climate change. Scores close to 1.0 represent strong agreement, while those around 0.5 indicate moderate agreement.

Negative Scores: Scores down to −0.5 reveal respondents with higher levels of doubt and disagreement. These negative scores suggest that indeterminacy and falsehood values outweigh the truth values in these responses, reflecting significant uncertainty and conflicting beliefs.

From an agnostology perspective, the distribution of scores, particularly the presence of negative values, underscores the prevalent uncertainty and doubt among the public. This highlights the need for targeted communication and educational efforts to address these areas of ignorance and improve public understanding of climate science.

5 | Conclusion

The use of neutrosophy in this paper allows for a more detailed collection of public opinions, moving beyond simple binary responses to include degrees of uncertainty and ambivalence regarding the scientific consensus on climate change. Employing neutrosophic Likert scales provides deeper insights into the spectrum of perceptions and aids in evaluating their potential implications for effective communication and policy-making in addressing climate change challenges. Traditional statistical methods have been employed; however, the integration of neutrosophic statistics could offer more robust tools for analyzing complex data.

Future research should explore the application of neutrosophic approaches to other critical areas of public perception and policy, such as public health and socio-political issues, to capture a broader range of uncertainties and beliefs. By expanding the use of neutrosophic logic and statistics, researchers can better understand and address the intricacies of ignorance and misinformation, ultimately improving educational strategies and policy interventions. This could pave the way for more comprehensive and inclusive models of public understanding and engagement in various domains.

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Author Contribution

All authors contributed equally to this work.

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Data Availability

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

Conflicts of Interest

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

Ethical Approval

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

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