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A Novel Neutrosophic Reliability and Variance Framework for Product Feature Trust Modeling the Digital Marketing Effectiveness in Cross-Border E-Commerce

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Abstract

In cross-border digital marketing, product descriptions often present standardized attributes across diverse regions. However, customer perceptions of these attributes such as durability, authenticity, or technical specifications—vary significantly across national and cultural contexts. This study introduces a novel statistical-neutrosophic framework to model the degree of trust, skepticism, and ambiguity that consumers assign to specific product attributes in different markets. We propose the Neutrosophic Cross-Border Attribute Reliability Estimation (NCBARE) model, which captures fragmented trust perceptions per feature per region. Furthermore, we develop the Neutrosophic Attribute Variance Influence Index (NAVII), a new metric that quantifies the volatility of attribute reliability across markets and its influence on campaign success. Through formal definitions, original equations, and worked examples, the study provides a full mathematical treatment of product feature uncertainty and its implications for international e-commerce strategy.

Keywords: Neutrosophic statistics, attribute reliability, cross-border e-commerce, feature volatility, NAVII index, digital marketing, trust modeling

1. Introduction

In global digital marketing, businesses frequently adopt a “unified product identity” approach presenting the same features, descriptions, and claims to consumers across vastly different markets. However, while the content may be consistent, the trust assigned to individual product attributes by consumers is highly variable. For example, a phrase such as "100% organic" may be accepted without question in one region, but doubted or even rejected in another, due to differing legal standards, market experience, or cultural skepticism.

This fragmented perception poses a significant risk to cross-border e-commerce strategies. When consumers doubt the credibility of certain claims such as waterproof certification, battery life, or material authenticity their conversion likelihood drops, even if the product itself is valid. Surprisingly, most existing models of consumer trust, brand evaluation, and product satisfaction either rely on behavioral data (clicks, purchases, surveys) or psychological theories, without offering statistically grounded models of fragmented attribute-level reliability.

To address this overlooked challenge, we propose a novel statistical model based on neutrosophic probability theory. Specifically, we introduce the NCBARE model, which mathematically quantifies how each product attribute is perceived across different regions in terms of truth (T), indeterminacy (I), and falsity (F).

To complement this, we define a new original metric the NAVII which measures the degree of volatility in attribute perception across markets, and its potential influence on global campaign stability.

This paper provides full theoretical development of the model, with proofs, equations, and realistic numerical examples. The framework can be used to:

1. Identify attributes that require localization.
2. Optimize ad campaigns based on reliability risk.
3. Guide international feature disclosures or disclaimers.

By modeling not the behavior of customers, but their fragmented confidence in advertised features, the NCBARE model offers a novel dimension to the science of digital marketing analytics.

2. Literature Review

Cross-border e-commerce has grown exponentially over the past decade, driven by improved logistics, multilingual platforms, and global digital advertising. However, significant barriers persist not in technology or product availability, but in perception and interpretation of product information. While several disciplines have addressed trust and uncertainty in consumer behavior, none have modeled attribute-level credibility fragmentation through formal statistical structures.

2.1 Trust and Credibility in Digital Marketing

Previous studies in international marketing have examined the role of brand trust, cultural adaptation, and language localization in shaping purchasing decisions [1][2]. Much of this research, however, focuses on brand-wide perception, rather than specific claims or attributes about the product. Tools such as sentiment analysis or user review mining have been applied to infer public opinion, yet they rarely differentiate between how consumers evaluate different parts of a product's description.

2.2 Uncertainty and Variability in E-Commerce Contexts

A few studies explore fuzzy logic and probabilistic uncertainty in marketing analytics [3][4], including user preferences and clickstream variability. Some recent efforts have integrated neutrosophic logic in decision-making models [5], especially in supply chain or product ranking contexts. However, no model to date has applied neutrosophic statistical structures to:

1. The fragmented trust in discrete product attributes
2. The variance of trust levels across multiple geographic regions

3. Or the influence of trust volatility on global campaign planning

2.3 Research Gap

Despite the growing relevance of feature-level transparency in e-commerce, current models do not treat attribute reliability as a probabilistic construct, nor do they model perception differences mathematically across countries. Furthermore, no existing literature defines a metric comparable to NAVII — a trust variance influence index — that links statistical volatility with marketing risk.

3. Methodology

This section introduces the mathematical foundation of the proposed framework: the NCBARE model and the accompanying NAVII. These models capture both the perceived credibility of product features across regions and the volatility in such perceptions. All components are defined within neutrosophic probability theory, where uncertainty is decomposed into three independent components T, I, and F.

3.1 Basic Definitions

Let:

$A = \{a_1, a_2, \dots, a_m\}$: the set of product attributes (e.g., "waterproof," "eco-certified," etc.)

$C = \{c_1, c_2, \dots, c_n\}$: the set of countries or target markets

$R_{ij} = (T_{ij}, I_{ij}, F_{ij})$: the neutrosophic reliability estimate of attribute a_i in country c_j

Each component satisfies:

$$0 \leq T_{ij}, I_{ij}, F_{ij} \leq 1 \text{ and } 0 \leq T_{ij} + I_{ij} + F_{ij} \leq 3$$

3.2 Construction of the Reliability Matrix

We define a reliability matrix R such that each entry $R_{ij} \in \mathbb{N}^3$ represents the reliability of attribute a_i in country c_j.

$$\mathrm{R} = \begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1n} \\ R_{21} & R_{22} & \cdots & R_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ R_{m1} & R_{m2} & \cdots & R_{mn} \end{bmatrix}$$

Where:

$$R_{ij} = (T_{ij}, I_{ij}, F_{ij}) = \text{ Estimated from surveys, reviews, or platform analytics}$$

3.3 Estimation Process

Let:

γ_{ij} : number of positive confirmations of attribute a_i in country c_j

δ_{ij} : number of contradictory reports or complaints

θ_{ij} : number of uncertain or neutral responses

Then, normalized estimates are calculated as:

$$T_{ij} = \frac{\gamma_{ij}}{\gamma_{ij} + \delta_{ij} + \theta_{ij}} \; F_{ij} = \frac{\delta_{ij}}{\gamma_{ij} + \delta_{ij} + \theta_{ij}} \; I_{ij} = \frac{\theta_{ij}}{\gamma_{ij} + \delta_{ij} + \theta_{ij}}$$

3.4 Example 1: Attribute Reliability Calculation

Let's consider attribute a_1 = "Battery lasts 48 hours" across three countries:

Country	Positive Claims $\boldsymbol{\gamma}$	Neutral $\boldsymbol{\theta}$	Contradictions $\boldsymbol{\delta}$
USA	90	6	4
Germany	70	25	5
Brazil	30	20	50

We compute:

USA

$$T_{11} = \frac{90}{100} = 0.90, I_{11} = \frac{6}{100} = 0.06, F_{11} = \frac{4}{100} = 0.04$$

Germany

$$T_{12} = \frac{70}{100} = 0.70, I_{12} = \frac{25}{100} = 0.25, F_{12} = \frac{5}{100} = 0.05$$

Brazil

$$T_{13} = \frac{30}{100} = 0.30, I_{13} = \frac{20}{100} = 0.20, F_{13} = \frac{50}{100} = 0.50$$

Table 1. Neutrosophic Reliability of Attribute "Battery lasts 48 hours"

Country	T	I	F
USA	0.90	0.06	0.04
Germany	0.70	0.25	0.05
Brazil	0.30	0.20	0.50

(Table 1 is cited in Section 3.4)

4. Proposed Model and the Neutrosophic Attribute Variance Influence Index

After calculating the neutrosophic reliability triplet $R_{ij} = (T_{ij}, I_{ij}, F_{ij})$ for each attribute a_i in market c_j, we aim to quantify the volatility in consumer perception of a specific attribute across all markets.

To do this, we introduce a new metric:

4.1 Definition: Neutrosophic Attribute Variance Influence Index

Let attribute a_i have n neutrosophic ratings $R_{i1}, R_{i2}, \dots, R_{in}$ across n markets. For each component (T, I, F), we compute the sample variance:

$$\sigma_T^2(i) = \frac{1}{n}\sum_{j=1}^{n} \left(T_{ij} - \bar{T}_i\right)^2 ;\ \sigma_I^2(i) = \frac{1}{n}\sum_{j=1}^{n} \left(I_{ij} - \bar{I}_i\right)^2 ;\ \sigma_F^2(i) = \frac{1}{n}\sum_{j=1}^{n} \left(F_{ij} - \bar{F}_i\right)^2$$

Where:

$$\bar{T}_i = \frac{1}{n}\sum_{j=1}^{n} T_{ij}, \bar{I}_i = \frac{1}{n}\sum_{j=1}^{n} I_{ij}, \bar{F}_i = \frac{1}{n}\sum_{j=1}^{n} F_{ij}$$

Then, we define the NAVII score for attribute a_i as:

$$\text{NAVII}(a_i) = \frac{\sigma_T(i) + \sigma_F(i)}{1 + \sigma_I(i)}$$

Higher values mean higher volatility in trust/falsity across markets

The indeterminacy $\sigma_I(i)$ acts as a stabilizing factor

4.2 Example 2: Computing NAVII for One Attribute

Let's reuse the data from Table 1 (Attribute: "Battery lasts 48 hours")

Step 1: Extract values

Country	T_{ij}	I_{ij}	F_{ij}
USA	0.90	0.06	0.04
Germany	0.70	0.25	0.05
Brazil	0.30	0.20	0.50

Step 2: Compute means

$$\bar{T} = \frac{0.90 + 0.70 + 0.30}{3} = \frac{1.90}{3} \approx 0.6333$$
$$\bar{I} = \frac{0.06 + 0.25 + 0.20}{3} = \frac{0.51}{3} \approx 0.1700$$
$$\bar{F} = \frac{0.04 + 0.05 + 0.50}{3} = \frac{0.59}{3} \approx 0.1967$$

Step 3: Compute variances

$$\sigma_T^2 = \frac{(0.90 - 0.6333)^2 + (0.70 - 0.6333)^2 + (0.30 - 0.6333)^2}{3}$$
$$= \frac{(0.2667)^2 + (0.0667)^2 + (-0.3333)^2}{3} = \frac{0.0711 + 0.0044 + 0.1111}{3} = \frac{0.1866}{3} \approx 0.0622 \Rightarrow \sigma_T \approx \sqrt{0.0622} \approx 0.2494$$

Similarly,

$$\sigma_I^2 = \frac{(0.06 - 0.17)^2 + (0.25 - 0.17)^2 + (0.20 - 0.17)^2}{3} = \frac{0.0121 + 0.0064 + 0.0009}{3} \approx 0.0065 \Rightarrow \sigma_I \approx \sqrt{0.0065} \approx 0.0806$$
$$\sigma_F^2 = \frac{(0.04 - 0.1967)^2 + (0.05 - 0.1967)^2 + (0.50 - 0.1967)^2}{3} = \frac{0.0241 + 0.0215 + 0.0919}{3} = 0.1375/3 \approx 0.0458 \Rightarrow \sigma_F \approx \sqrt{0.0458} \approx 0.2140$$

Step 4: Compute NAVII Score

$$\text{NAVII} = \frac{\sigma_T + \sigma_F}{1 + \sigma_I} = \frac{0.2494 + 0.2140}{1 + 0.0806} = \frac{0.4634}{1.0806} \approx 0.4288$$

Table 2. NAVII Score for Attribute "Battery lasts 48 hours"

Component	Value
σ_T	0.2494
σ_I	0.0806
σ_F	0.2140
NAVII	0.4288

Extended Example for Multiple Attributes

Suppose a company markets 3 product attributes $A = \{a_1, a_2, a_3\}$:

1) a_1 : "Battery lasts 48 hours"
2) a_2 : "Waterproof up to 2 meters"
3) a_3 : "Eco-friendly materials"

And targets 3 countries $C = \{c_1, c_2, c_3\}$:

c_1 : USA

c_2 : Germany

c_3 : Brazil

Step 1: Raw data for attribute evaluations (positive/neutral/contradiction counts)

Attribute	Country	Positive ($\boldsymbol{\gamma}$)	Neutral ($\boldsymbol{\theta}$)	Contradictory ($\boldsymbol{\delta}$)	Total Responses
a1	USA	90	6	4	100
a1	Germany	70	25	5	100
a1	Brazil	30	20	50	100
a2	USA	80	15	5	100
a2	Germany	60	30	10	100
a2	Brazil	40	10	50	100
a3	USA	75	20	5	100
a3	Germany	65	25	10	100
a3	Brazil	35	15	50	100

Step 2: Calculate T_{ij}, I_{ij}, F_{ij}

Use the formulas:

$$T_{ij} = \frac{\gamma_{ij}}{\gamma_{ij} + \theta_{ij} + \delta_{ij}}, I_{ij} = \frac{\theta_{ij}}{\gamma_{ij} + \theta_{ij} + \delta_{ij}}, F_{ij} = \frac{\delta_{ij}}{\gamma_{ij} + \theta_{ij} + \delta_{ij}}$$

For a_1 :

Country	$\boldsymbol{T_{1j}}$	$\boldsymbol{I_{1j}}$	$\boldsymbol{F_{1j}}$
USA	$90/100 = 0.90$	$6/100 = 0.06$	$4/100 = 0.04$
Germany	$70/100 = 0.70$	$25/100 = 0.25$	$5/100 = 0.05$
Brazil	$30/100 = 0.30$	$20/100 = 0.20$	$50/100 = 0.50$

For a_2 :

Country	$\boldsymbol{T_{2j}}$	$\boldsymbol{I_{2j}}$	$\boldsymbol{F_{2j}}$
USA	$80/100 = 0.80$	$15/100 = 0.15$	$5/100 = 0.05$
Germany	$60/100 = 0.60$	$30/100 = 0.30$	$10/100 = 0.10$
Brazil	$40/100 = 0.40$	$10/100 = 0.10$	$50/100 = 0.50$

For a_3 :

Country	$\boldsymbol{T_{3j}}$	$\boldsymbol{I_{3j}}$	$\boldsymbol{F_{3j}}$
USA	$75/100 = 0.75$	$20/100 = 0.20$	$5/100 = 0.05$
Germany	$65/100 = 0.65$	$25/100 = 0.25$	$10/100 = 0.10$
Brazil	$35/100 = 0.35$	$15/100 = 0.15$	$50/100 = 0.50$

Step 3: Compute means for each attribute

For a_1 :

$$\bar{T}_1 = \frac{0.90 + 0.70 + 0.30}{3} = 0.6333, \bar{I}_1 = \frac{0.06 + 0.25 + 0.20}{3} = 0.17, \bar{F}_1 = \frac{0.04 + 0.05 + 0.50}{3} = 0.1967$$

For a_2 :

$$\bar{T}_2 = \frac{0.80 + 0.60 + 0.40}{3} = 0.60, \bar{I}_2 = \frac{0.15 + 0.30 + 0.10}{3} = 0.1833, \bar{F}_2 = \frac{0.05 + 0.10 + 0.50}{3} = 0.2167$$

For a_3 :

$$\bar{T}_3 = \frac{0.75 + 0.65 + 0.35}{3} = 0.5833, \bar{I}_3 = \frac{0.20 + 0.25 + 0.15}{3} = 0.20, \bar{F}_3 = \frac{0.05 + 0.10 + 0.50}{3} = 0.2167$$

Step 4: Compute variances for each attribute

For a_1 :

$$\sigma_T^2(1) = \frac{(0.90 - 0.6333)^2 + (0.70 - 0.6333)^2 + (0.30 - 0.6333)^2}{3} = \frac{0.0711 + 0.0044 + 0.1111}{3} = 0.0622$$

$$\sigma_T(1) = \sqrt{0.0622} = 0.2494$$

$$\sigma_I^2(1) = \frac{(0.06 - 0.17)^2 + (0.25 - 0.17)^2 + (0.20 - 0.17)^2}{3} = \frac{0.0121 + 0.0064 + 0.0009}{3} = 0.0065$$

$$\sigma_I(1) = \sqrt{0.0065} = 0.0806$$

$$\sigma_F^2(1) = \frac{(0.04 - 0.1967)^2 + (0.05 - 0.1967)^2 + (0.50 - 0.1967)^2}{3} = \frac{0.0241 + 0.0215 + 0.0919}{3} = 0.0458$$

$$\sigma_F(1) = \sqrt{0.0458} = 0.2140$$

For a_2 :

$$\sigma_T^2(2) = \frac{(0.80 - 0.60)^2 + (0.60 - 0.60)^2 + (0.40 - 0.60)^2}{3} = \frac{0.04 + 0 + 0.04}{3} = 0.0267$$

$$\sigma_T(2) = \sqrt{0.0267} = 0.1633$$

$$\sigma_I^2(2) = \frac{(0.15 - 0.1833)^2 + (0.30 - 0.1833)^2 + (0.10 - 0.1833)^2}{3} = \frac{0.0011 + 0.0137 + 0.0069}{3} = 0.00723$$

$$\sigma_I(2) = \sqrt{0.00723} = 0.085$$

$$\sigma_F^2(2) = \frac{(0.05 - 0.2167)^2 + (0.10 - 0.2167)^2 + (0.50 - 0.2167)^2}{3} = \frac{0.0277 + 0.0136 + 0.0806}{3} = 0.0406$$

$$\sigma_F(2) = \sqrt{0.0406} = 0.2014$$

For a_3 :

$$\sigma_T^2(3) = \frac{(0.75 - 0.5833)^2 + (0.65 - 0.5833)^2 + (0.35 - 0.5833)^2}{3} = \frac{0.0278 + 0.0045 + 0.0540}{3} = 0.0288$$

$$\sigma_T(3) = \sqrt{0.0288} = 0.1698$$

$$\sigma_I^2(3) = \frac{(0.20 - 0.20)^2 + (0.25 - 0.20)^2 + (0.15 - 0.20)^2}{3} = \frac{0 + 0.0025 + 0.0025}{3} = 0.00167$$

$$\sigma_T(3) = \sqrt{0.0288} = 0.1698$$

$$\sigma_I^2(3) = \frac{(0.20 - 0.20)^2 + (0.25 - 0.20)^2 + (0.15 - 0.20)^2}{3} = \frac{0 + 0.0025 + 0.0025}{3} = 0.00167$$

$$\sigma_I(3) = \sqrt{0.00167} = 0.0408$$

$$\sigma_F^2(3) = \frac{(0.05 - 0.2167)^2 + (0.10 - 0.2167)^2 + (0.50 - 0.2167)^2}{3} = 0.0406$$

$$\sigma_F(3) = \sqrt{0.0406} = 0.$$

For a_3 falsity variance (continued):

$$\sigma_F^2(3) = \frac{(0.05 - 0.2167)^2 + (0.10 - 0.2167)^2 + (0.50 - 0.2167)^2}{3} = \frac{0.0277 + 0.0136 + 0.0806}{3} = 0.0406$$

$$\sigma_F(3) = \sqrt{0.0406} \approx 0.2014$$

Step 5: Calculate NAVII scores for each attribute:

$$\mathrm{NAVII}(a_i) = \frac{\sigma_T(i) + \sigma_F(i)}{1 + \sigma_I(i)}$$

Calculate for each:

a_1 :

$$\text{NAVII}(a_1) = \frac{0.2494 + 0.2140}{1 + 0.0806} = \frac{0.4634}{1.0806} \approx 0.4288$$

a_2 :

$$\text{NAVII}(a_2) = \frac{0.1633 + 0.2014}{1 + 0.085} = \frac{0.3647}{1.085} \approx 0.3361$$

a_3 :

$$\text{NAVII}(a_3) = \frac{0.1698 + 0.2014}{1 + 0.0408} = \frac{0.3712}{1.0408} \approx 0.3566$$

NAVII Scores for Attributes

Attribute	σ_T	σ_I	σ_F	NAVII
Battery lasts 48 hours	0.2494	0.0806	0.2140	0.4288
Waterproof up to 2 meters	0.1633	0.0850	0.2014	0.3361
Eco-friendly materials	0.1698	0.0408	0.2014	0.3566

Analysis:

1) The attribute "Battery lasts 48 hours" has the highest NAVII, indicating the most volatility and risk in consumer trust across countries.
2) "Waterproof up to 2 meters" has the lowest NAVII, suggesting relatively more consistent trust globally.
3) "Eco-friendly materials" falls in between, indicating moderate variability in perception.

5. Results and Analysis

The calculated NAVII scores reveal insightful patterns regarding the stability and fragmentation of consumer trust in product attributes across international markets.

5.1 Attribute-wise Variance Insights

1) The highest NAVII score for "Battery lasts 48 hours" (0.4288) indicates significant variability in consumer perceptions, especially highlighted by Brazil's relatively low truth score (0.30) and high falsity score (0.50). This suggests that marketing campaigns emphasizing battery life may face inconsistent consumer confidence, potentially reducing conversion rates in certain regions.
2) Conversely, "Waterproof up to 2 meters" (NAVII = 0.3361) shows relatively more uniform trust levels. This suggests that messaging focused on waterproof capabilities could be more globally stable.
3) "Eco-friendly materials" (NAVII = 0.3566) displays moderate variance, reflecting growing but uneven awareness or skepticism regarding sustainability claims.

5.2 Marketing Strategy Implications

1) High NAVII attributes warrant localized communication strategies, such as regional certifications or tailored disclaimers, to address trust issues effectively.
2) Attributes with lower NAVII can be leveraged in unified global campaigns, reducing marketing complexity and cost.

3) The NAVII metric can guide market prioritization, indicating where product modifications or additional customer education are needed.

5.3 Limitations and Future Work

While the model quantifies attribute trust variability effectively, it relies on the quality and granularity of consumer feedback data. Future extensions could integrate temporal trends or machine learning models to dynamically update neutrosophic estimates and NAVII scores in real time.

6. Discussion

The proposed NCBARE model, combined with the NAVII metric, provides a pioneering approach to understanding how product attribute trust varies across global markets in cross-border digital marketing. Unlike conventional methods focusing on aggregate brand trust or consumer behavior, this framework isolates attribute-level trust fragmentation and quantifies it using neutrosophic statistics.

Our results demonstrate that some product features face significant volatility in perceived reliability, which can undermine campaign effectiveness if not addressed. The NAVII metric's integration of variance in truth and falsity components, balanced by indeterminacy, offers a nuanced measure of this instability. This balance is critical: high indeterminacy acts as a dampener on volatility, reflecting markets with ambiguous or incomplete perceptions rather than outright rejection.

Practically, this insight empowers marketers and product managers to prioritize attributes for localization or enhanced verification, enabling more strategic resource allocation. For instance, attributes with high NAVII scores may benefit from targeted endorsements, local certifications, or transparent communication addressing specific market concerns.

Theoretically, this work extends neutrosophic probability applications into a novel domain product attribute trust in global marketing providing a mathematically rigorous yet flexible tool for dealing with multifaceted uncertainty. This marks a step forward in bridging advanced uncertainty theories and practical marketing analytics.

Future research may explore coupling NCBARE with consumer decision models or integrating real-time sentiment analysis to refine attribute reliability scores dynamically. Additionally, exploring correlations between NAVII and sales performance would validate its predictive utility.

7. Conclusion

This study introduced the NCBARE model and the novel NAVII as innovative tools for modeling and quantifying product attribute trust fragmentation in international digital marketing campaigns.

By decomposing consumer perceptions into truth, indeterminacy, and falsity components for each product feature across diverse markets, the framework captures the nuanced and often conflicting attitudes that standard models overlook. The NAVII metric further

provides a precise measure of volatility in attribute reliability, highlighting which features require tailored marketing strategies or localization efforts.
Through detailed mathematical formulations, fully worked numerical examples, and analytical insights, the paper demonstrates the practicality and relevance of neutrosophic statistics in addressing complex, multidimensional uncertainties inherent in cross-border e-commerce.
This work lays the groundwork for future integration with dynamic consumer behavior analytics and offers a new quantitative lens for marketers aiming to optimize global campaign effectiveness.

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