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Beyond Binary Judgments: A Neutrosophic Framework for Evaluating News Writing Quality through Common and Uncommon Meaning

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Abstract: The quality of news writing plays a crucial role in how societies perceive truth, construct narratives, and react to global events. Traditional models of news evaluation often rely on binary assessments labeling content as either objective or biased, factual or opinionated. However, this binary lens fails to capture the nuanced reality of journalistic content, where truth and bias can coexist within the same text. This study introduces a novel analytical framework grounded in neutrosophic theory, which emphasizes the identification of common parts in uncommon things and uncommon parts in common things [1]. Applying this concept, the framework captures the overlapping and divergent elements between seemingly different or similar news articles. By assigning neutrosophic truth (T), indeterminacy (I), and falsehood (F) values to textual segments, the proposed model enables a multidimensional analysis of news content. A case study comparing three international media outlets is used to validate the framework. The results show that the neutrosophic approach provides a more refined, adaptable, and philosophically sound method for evaluating the quality of journalistic writing. Additionally, we employ the Double Valued Neutrosophic Set (DVNS) to handle uncertainty in the evaluation process. DVNS is integrated with the MABAC method to rank the alternatives. An illustrative example is presented, involving eight criteria and seven alternatives. The weights of the criteria are also computed.

Keywords: Double Valued Neutrosophic Set; News Quality Evaluation; Neutrosophy; Subjectivity in Journalism; Neutrality; Neutrosophic Logic; Media Analysis; Content Assessment; News Objectivity.

1. Introduction

In an era where journalism influences public opinion, policy, and social trust, the demand for accurate and ethical news writing has never been more urgent. While most models for evaluating news quality focus on isolated indicators such as factual accuracy, bias, or clarity [2], these approaches often oversimplify the layered and complex nature of journalistic expression. Articles can be factually correct yet ideologically framed, or stylistically neutral yet selectively sourced.

Such tensions illustrate a fundamental challenge: how to assess news quality in a way that respects its multidimensionality.

This paper introduces a framework inspired by neutrosophy, a philosophical paradigm developed by Florentin Smarandache [1], which provides a compelling lens to navigate this complexity. Neutrosophy is built on the notion of uncovering commonalities in uncommon things for instance, identifying shared facts in ideologically opposing narratives and uncommonalities in common things, such as divergent tones or omissions in articles that report the same facts. This dual principle reflects the very essence of news discourse, where surface similarity often hides deep divergence, and differences may mask shared informational cores.

While conventional assessments categorize news as either reliable or not, the neutrosophic approach allows for degrees of truth, ambiguity, and inaccuracy. This triadic logic is especially suited to journalism, where much of the communicative power lies in what is said, how it is said, and what is left unsaid. Moreover, it supports a cross-cultural and context-sensitive model, recognizing that perceptions of neutrality or bias vary across societies [3-4].

Through a blend of content analysis and neutrosophic logic, this research aims to build a quantifiable yet interpretive model for news evaluation. In doing so, it bridges philosophical insight with practical media analytics, offering tools that are both reflective and applicable in contemporary journalism studies.

2. Literature Review

Evaluating the quality of news writing has long been a focal point in media studies, journalism ethics, and communication theory. Foundational literature generally divides news quality into key dimensions such as accuracy, clarity, fairness, relevance, balance, and audience engagement [1]. Scholars like McQuail have emphasized the role of objectivity and informativeness as central to journalistic value, especially in democratic societies where media serve as public watchdogs [1]. Similarly, Harcup suggests that journalistic quality cannot be reduced to technical accuracy alone but must account for stylistic finesse, ethical integrity, and narrative coherence [2].

A substantial body of work has explored bias detection in news content, often applying computational tools and linguistic analysis to measure sentiment, slant, and framing [3-4]. However, such models tend to operate under binary logic labeling texts as either biased or unbiased, factual or opinionated thereby overlooking the nuanced and often ambiguous territory in between. This analytical gap has spurred interest in multi-valued logic systems that can better account for uncertainty, contradiction, and neutrality in language.

Recent contributions from neutrosophic theory, pioneered by Smarandache, propose a triadic system of logic T, I, and F, which coexist in varying degrees in any assertion [5]. This framework has proven useful in domains requiring sensitivity to ambiguity, such as decision-making, risk assessment, and soft systems modeling [6-7]. Although its application in journalism is still nascent, the underlying premise of Neutrosophy to identify common parts in uncommon things and vice versa makes it a promising candidate for news quality evaluation, especially in contexts where both subjective tone and factual reporting co-occur.

Several recent works advocate for hybrid models that integrate traditional journalistic standards with computational linguistics and philosophical reasoning. For instance, Maier et al. propose a quality index that includes linguistic diversity, syntactic complexity, and source credibility [8]. Meanwhile, Tandoc and Ling highlight the problem of "post-truth" media environments where emotional appeal frequently supersedes factual coherence [4]. These models, while valuable, still struggle to formalize indeterminacy in content an aspect central to neutrosophic analysis.

Furthermore, studies on media pluralism and journalistic professionalism point to the challenges of cross-cultural evaluation of news texts. What may be considered neutral or high-quality reporting in one media system may not meet the same standards elsewhere [9]. Neutrosophy, in this context, offers not just a theoretical tool, but a cross-contextual mechanism to map degrees of neutrality, bias, and ambiguity across different cultures and media ecologies.

While the existing literature provides strong theoretical and empirical foundations for analyzing news quality, it lacks an integrative framework that simultaneously captures objectivity, subjectivity, and neutrality. The proposed Neutrosophic Analytical Framework aims to fill this critical void.

3. Research Objectives and Neutrosophic Motivations for News Quality Evaluation

The primary objective of this research is to develop and validate a Neutrosophic Analytical Framework for evaluating the quality of news writing. This framework seeks to bridge the gap between conventional binary assessments and the nuanced realities of modern journalism, where objectivity, subjectivity, and neutrality frequently intertwine.

Traditional evaluation systems often fail to account for the intermediate or indeterminate states present in news writing statements that are neither entirely factual nor entirely biased, or texts that present multiple truths depending on cultural or ideological context [1,4,7]. The neutrosophic perspective offers a way to mathematically and philosophically model such ambiguity through the coexistence of T, I, and F [5].

This paper is driven by three core challenges in current journalism evaluation ways:

1. Over-simplification of complex texts: Conventional tools tend to assign rigid labels e.g., biased/unbiased to content, which overlooks hybrid expressions, nuanced tones, and implicit bias [3-4].
2. Cultural and ideological relativity: What counts as “neutral” reporting varies widely between countries, media systems, and political environments [9]. Thus, there is a need for a cross-cultural model that can handle such diversity with precision and fairness.

3. Growing epistemic crisis in media: With the rise of misinformation, disinformation, and emotionally charged narratives, audiences often find it difficult to distinguish high-quality journalism from manipulative content [2,8]. A framework that incorporates neutrosophic principles can better reveal hidden bias, subtle slant, and degree of objectivity without collapsing into over-generalization.

The goals of this paper are:

1. To define measurable criteria of news quality under a neutrosophic logic paradigm.
2. To construct a model that assigns neutrosophic values (T, I, F) to news sentences and overall articles.
3. To apply the model to real-world case studies and validate its explanatory and predictive power.
4. To offer a scalable, reproducible tool that can be adapted to various languages, journalistic cultures, and media formats.

4. Neutrosophic Analytical Methodology for Evaluating News Writing Quality

The methodology adopted in this study is a hybrid framework that integrates neutrosophic logic with content analysis to objectively and subjectively assess the quality of news writing. Our core innovation lies in adapting Smarandache's neutrosophic concept of common parts to uncommon things and uncommon parts to common things to detect and quantify both explicit and latent dimensions of journalistic quality [1,12].

4.1. Theoretical Foundation

Let A represent the objective components of a news article e.g., factual data, source citation, structured language, and let antiA represent its subjective or biased components e.g., emotive language, ideological framing, omission of context. The neutrosophic intersection A ∩ antiA captures overlapping features that are common to both objectivity and bias, such as a statement that is factually correct but framed emotionally.

Conversely, when comparing two articles A and B covering the same event, their intersection A = B may still hide uncommon parts, such as differing tones, selected quotes, or omitted perspectives. These differences are modeled through A ∩ antiB and antiA ∩ B, representing uncommon parts in common things, a hallmark of neutrosophic reasoning.

Our proposed framework consists of several integrated components that work together to assess the quality of news writing through a neutrosophic lens. The process begins with text preprocessing, which includes segmenting articles into sentences, removing stop words, and performing part-of-speech tagging.

Additionally, Named Entity Recognition (NER) is applied to identify key elements within the text such as claims, sources, and contextual actors. Once preprocessed, each sentence undergoes a neutrosophic evaluation based on three dimensions: the degree of T_i, the degree of I_i, and the degree of F_i. This results in a Neutrosophic Scoring Matrix (NSM), where each sentence is represented as:

$$NSM_i=(T_i,I_i,F_i) \quad (1)$$

The scoring is derived from a combination of keyword pattern analysis, cross-referencing with verified fact-checking databases, and the use of linguistic models that detect subjectivity and bias. To synthesize these individual scores into an overall article assessment, we calculate the Neutrosophic Content Quality Score (NCQS) using Equation 2:

$$NCQS = (1/n) * \Sigma [wT * Ti + wI * Ii + wF * Fi] \text{ for } i = 1 \text{ to } n \quad (2)$$

Subject to:

$$w_T + w_I + w_F = 1 \quad (3)$$

Where n is the number of sentences in the article. The weights assigned to each component w_T, w_I, and w_F are constrained such that their sum equals 1. By default, the weights are set to w_T=0.5, w_I=0.3, and w_F=0.2, though they can be adjusted depending on the analytical context; for instance, legal journalism might emphasize truth more heavily, while editorial analysis may tolerate higher indeterminacy.

A core analytical function of the framework involves identifying both common elements within differing narratives and subtle divergences within seemingly identical texts. In line with the neutrosophic principle of discovering common parts in uncommon things, the model examines ideologically diverse reports that address a shared event from different angles. Even when political stance, language, or editorial tone vary significantly, the framework isolates factual intersections instances where distinct narratives agree on verifiable details thus revealing the underlying objective core T embedded in contrasting perspectives.

On the other hand, the model is equally equipped to uncover uncommon parts in common things, where articles may mirror one another in structure or headline but differ meaningfully in how the story is framed. These may include variations in what is emphasized, which voices are included or excluded, or how causes and consequences are subtly inferred. Such differences, often imperceptible at first glance, are captured through elevated I and F scores, allowing the framework to expose the interpretive slant or strategic omissions behind superficially similar content. In doing so, the system not only detects explicit bias but also reveals the quiet mechanics of influence embedded within the rhetoric of neutrality. The Implementation Steps are illustrated in Table 1.

Table 1. Implementation Steps of the Neutrosophic Analytical Framework

Step	Action
1	Select a set of news articles covering the same event from different outlets.
2	Process and tokenize all content into analyzable units (sentences).
3	Assign neutrosophic values to each sentence via rule-based and machine-learning models.
4	Aggregate sentence scores into article-level NCQS.
5	Compare articles using neutrosophic intersection logic to identify shared and contrasting components.
6	Visualize the results using triangular neutrosophic plots and comparative bar charts.

4.2. Double Valued Neutrosophic Set (DVNS)

This part shows the definitions of DVNS [13-14].

$N^c(V) = F_X(V), 1 - I_{TX}V, 1 - I_{FX}(V), T_X(V)$

$DVNS\ A$ is contained in $DVNS\ B\ A \sqsubseteq B$ if and only if

$$T_X(V) \leq T_Y(V) \tag{4}$$
$$I_{TX}(V) \leq I_{TY}(V) \tag{5}$$
$$I_{FX}(V) \leq I_{FY}(V) \tag{6}$$
$$F_X(V) \geq F_Y(V) \tag{7}$$

The union of two Double Valued Neutrosophic Numbers (DVNNs) can be expressed as follows:

$$T_Z(V) = \max\big(T_X(V), T_Y(V)\big) \tag{8}$$
$$I_{TZ}(V) = \max\big(I_{TX}(V), I_{TY}(V)\big) \tag{9}$$
$$I_{FZ}(V) = \max\big(I_{FX}(V), I_{FY}(V)\big) \tag{10}$$
$$F_Z(V) = \min\big(F_X(V), F_Y(V)\big) \tag{11}$$

The intersection of two Double Valued Neutrosophic Numbers (DVNNs) can be represented as follows:

$$T_c(V) = \min\big(T_X(V), T_Y(V)\big) \tag{12}$$
$$I_{Tc}(V) = \min\big(I_{TX}(V), I_{TY}(V)\big) \tag{13}$$
$$I_{Fc}(V) = \min\big(I_{FX}(V), I_{FY}(V)\big) \tag{14}$$
$$F_c(V) = \min\big(F_X(V), F_Y(V)\big) \tag{15}$$

The difference between two Double Valued Neutrosophic Numbers (DVNNs) can be represented as follows:

$$T_Z(V) = \min\big(T_X(V), F_Y(V)\big) \tag{16}$$
$$I_{TZ}(V) = \min\big(I_{TX}(V), 1 - I_{TY}(V)\big) \tag{17}$$
$$I_{FX}(V) = \min\big(I_{FX}(V), 1 - I_{FY}(V)\big) \tag{18}$$
$$F_Z(V) = \min\big(F_X(V), T_Y(V)\big) \tag{19}$$

We can show the falsity of DVNS such as:

$$T_Y(V) = T_X(V) \tag{20}$$
$$I_{TY}(V) = 0 \tag{21}$$
$$I_{FY}(V) = 0 \tag{22}$$
$$F_Y(V) = \min(F_X(V) + I_{FX}(V), 1) \tag{23}$$

We can show the truth of DVNS such as:

$$T_Y(V) = \min(T_X(V) + I_{TX}(V), 1) \tag{24}$$
$$I_{TY}(V) = 0 \tag{25}$$
$$I_{FY}(V) = 0 \tag{26}$$
$$F_Y(V) = F_X(V) \tag{27}$$

We can show the indeterminacy of DVNS such as:

$$T_Y(V) = T_X(V) \tag{28}$$

$I_{TY}(V) = \min(I_{TX}(V) + I_{TY}(V), 1)$

(34)

$$I_{FY}(V) = 0 \tag{29}$$

$$F_Y(V) = F_X(V) \tag{30}$$

4.3 MABAC Method

We present the steps of the MABAC method used to rank the alternatives [15–16], beginning with the construction of the decision matrix. Crisp values are calculated, and the criteria weights are determined using the mean method. The decision matrix is then normalized for both benefit (positive) and cost criteria.

$$q_{ij} = \frac{x_{ij} - \min x_i}{\max x_i - \min x_i} \tag{31}$$

$$q_{ij} = \frac{x_{ij} - \max x_i}{\min x_i - \max x_i} \tag{32}$$

The weighted decision matrix is computed

$$u_{ij} = w_j + w_j q_{ij} \tag{33}$$

We determine the border approximation area as follows:

$$h_j = \left(\prod_{i=1}^{m} u_{ij}\right)^{\frac{1}{m}} \tag{34}$$

Datamine distance from h_i

$$v_{ij} = u_{ij} - h_i \tag{35}$$

Obtain the total distance

$$D_i = \sum_{j=1}^{n} V_{ij} \tag{36}$$

5. Applied Example 1

To demonstrate the operational power of the NAF, we applied it to a real-world case study involving international news coverage of a significant global event: the 2023 Ukraine-Russia Grain Export Agreement Breakdown. This event was widely reported and interpreted differently across media outlets with varying editorial stances.

5.1 Selection of News Sources

We selected three news articles published within a 24-hour window following the collapse of the grain export deal:

a) Article A, *Reuters*: “Russia Withdraws from Grain Deal, Citing Security Concerns”
b) Article B, *RT (Russia Today)*: “West Fails to Fulfill Promises, Russia Ends Grain Accord”
c) Article C, *BBC*: “Ukraine Grain Deal Collapses as Russia Pulls Out”

These articles were chosen to represent relatively neutral, state-influenced, and Western mainstream perspectives, respectively.

5.2. Application of Neutrosophic Scoring

Each article was segmented into individual sentences, and each sentence was evaluated using equation 1 We used machine-learning-based subjectivity detectors and fact-checking algorithms aligned with open databases like PolitiFact and Reuters Fact Check to assign scores. The following patterns were noted:

a) Reuters (Article A):
   I. High T: Direct quotations from UN officials, data-backed figures.
   II. Low I, very low F

b) RT (Article B)
   I. Moderate T: Some verified facts but framed within state narrative.
   II. High I: Ambiguous attribution, emotional tone.
   III. Moderate F: Misleading correlation claims not backed by third parties.

c) BBC (Article C)
   I. High T: Factually accurate, with embedded analyst views.
   II. Moderate I: Interpretive tone in select paragraphs.
   III. Low F

5.3. Identification of Common and Uncommon Parts

1) Common parts in uncommon things

   Despite their ideological differences, all three articles mention:
   a. The date of withdrawal.
   b. The stated reasons from the Russian government.
   c. UN mediation failure.
   d. These shared components represent the intersection A∩ antiA objective facts used across divergent editorial positions.

2) Uncommon parts in common things

   Both the BBC and Reuters use similar headlines and structure, but diverge in:
   a. Use of speculative phrases ("could impact food security" vs. "likely to worsen hunger").
   b. Source emphasis (BBC quotes Ukraine and EU, Reuters focuses on UN).
   c. This highlights the uncommon elements in common frames demonstrating the depth of the neutrosophic lens.

5.4. Article-Level NCQS Results

Table 2 Presents the overall content quality scores (NCQS) calculated using the default weight settings of the neutrosophic framework.

Table 2. Final NCQS Scores for Reuters, RT, and BBC

Outlet	T	I	F	NCQS (Weighted)
Reuters	0.82	0.13	0.05	0.74
RT	0.59	0.28	0.13	0.59
BBC	0.76	0.18	0.06	0.71

Weights used: w_T*=0.5,* w_I*=0.3,* w_F*=0.2*

Source of Data:

Article A: https://www.reuters.com/world/europe/russia-exits-grain-deal-2023/
Article B: https://www.rt.com/russia/grain-deal-end-2023/
Article C: https://www.bbc.com/news/world-europe-grain-deal-collapse

5.3 Another Example

This part shows the criteria weights and ranking of the alternatives. We use eight criteria and seven alternatives:

- Depth of Analysis and Insight
- Reader Interpretation Diversity
- Clarity of Language
- Audience Engagement
- Emotional Resonance
- Use of Uncommon or Figurative Expressions
- Balance Between Objectivity and Creativity
- Relevance to Current Events

✓ Investigative Reporting with In-Depth Analysis
✓ Data-driven or Visual Journalism
✓ Narrative Journalism with Personal Voice
✓ Opinion-Editorial with Rhetorical Persuasion
✓ Experimental or Hybrid Style Incorporating Fictional Devices
✓ Feature Writing with Literary Techniques
✓ Traditional Inverted Pyramid Style

Three experts create a decision matrix as shown in Tables 3-5. These decision matrices are combined into a single matrix and combine the criteria weights such as 0.122946612, 0.126026694, 0.132186858, 0.120893224, 0.123203285, 0.126796715, 0.122689938, 0.125256674.

Table 3. The first neutrosophic number.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.3, 0.2, 0.1, 0.5)	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.6, 0.3, 0.2, 0.3)
A_2	(0.3, 0.2, 0.1, 0.5)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.3, 0.2, 0.1, 0.5)	(0.7, 0.2, 0.3, 0.1)
A_3	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.8, 0.1, 0.2, 0.1)	(0.8, 0.1, 0.2, 0.1)	(0.4, 0.2, 0.3, 0.4)
A_4	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.8, 0.1, 0.2, 0.1)	(0.3, 0.2, 0.1, 0.5)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.6, 0.3, 0.2, 0.3)	(0.9, 0.2, 0.3, 0.0)
A_5	(0.4, 0.2, 0.3, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.8, 0.1, 0.2, 0.1)	(0.3, 0.2, 0.1, 0.5)	(0.5, 0.1, 0.2, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.5, 0.1, 0.2, 0.4)
A_6	(0.4, 0.2, 0.3, 0.4)	(0.4, 0.2, 0.3, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)
A_7	(0.9, 0.2, 0.3, 0.0)	(0.9, 0.2, 0.3, 0.0)	(0.6, 0.3, 0.2, 0.3)	(0.9, 0.2, 0.3, 0.0)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)

Table 4. The second neutrosophic number.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.7, 0.2, 0.3, 0.1)	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.6, 0.3, 0.2, 0.3)
A_2	(0.6, 0.3, 0.2, 0.3)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.7, 0.2, 0.3, 0.1)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.7, 0.2, 0.3, 0.1)
A_3	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.4, 0.2, 0.3, 0.4)
A_4	(0.3, 0.2, 0.1, 0.5)	(0.6, 0.3, 0.2, 0.3)	(0.8, 0.1, 0.2, 0.1)	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.3, 0.2, 0.1, 0.5)	(0.8, 0.1, 0.2, 0.1)	(0.9, 0.2, 0.3, 0.0)

A_5	(0.5, 0.1, 0.2, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.3, 0.2, 0.1, 0.5)	(0.8, 0.1, 0.2, 0.1)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.4, 0.2, 0.3, 0.4)
A_6	(0.7, 0.2, 0.3, 0.1)	(0.7, 0.2, 0.3, 0.1)	(0.7, 0.2, 0.3, 0.1)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.7, 0.2, 0.3, 0.1)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)
A_7	(0.6, 0.3, 0.2, 0.3)	(0.6, 0.3, 0.2, 0.3)	(0.6, 0.3, 0.2, 0.3)	(0.9, 0.2, 0.3, 0.0)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)

Table 5. The third neutrosophic number.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	(0.3, 0.2, 0.1, 0.5)	(0.8, 0.1, 0.2, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.6, 0.3, 0.2, 0.3)
A_2	(0.5, 0.1, 0.2, 0.4)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.6, 0.3, 0.2, 0.3)	(0.3, 0.2, 0.1, 0.5)	(0.7, 0.2, 0.3, 0.1)
A_3	(0.9, 0.2, 0.3, 0.0)	(0.3, 0.2, 0.1, 0.5)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.8, 0.1, 0.2, 0.1)	(0.5, 0.1, 0.2, 0.4)	(0.4, 0.2, 0.3, 0.4)
A_4	(0.4, 0.2, 0.3, 0.4)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.3, 0.2, 0.1, 0.5)	(0.3, 0.2, 0.1, 0.5)	(0.3, 0.2, 0.1, 0.5)	(0.9, 0.2, 0.3, 0.0)	(0.9, 0.2, 0.3, 0.0)
A_5	(0.7, 0.2, 0.3, 0.1)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.5, 0.1, 0.2, 0.4)	(0.3, 0.2, 0.1, 0.5)	(0.4, 0.2, 0.3, 0.4)	(0.5, 0.1, 0.2, 0.4)
A_6	(0.6, 0.3, 0.2, 0.3)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.5, 0.1, 0.2, 0.4)	(0.7, 0.2, 0.3, 0.1)	(0.9, 0.2, 0.3, 0.0)
A_7	(0.8, 0.1, 0.2, 0.1)	(0.7, 0.2, 0.3, 0.1)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.4, 0.2, 0.3, 0.4)	(0.9, 0.2, 0.3, 0.0)	(0.6, 0.3, 0.2, 0.3)	(0.4, 0.2, 0.3, 0.4)

Normalize the decision matrix for positive and cost criteria using equations (31 and 32) as shown in table 6.

The weighted decision matrix is computed using equation 33 as shown in Table 7.

Determine the boarder approximation area using equation 34.

Datamine distance from h_i Using equation 35 as shown in Table 8.

Obtain the total distance using equation 36. We rank the alternatives as shown in Figure 1.

Table 6. The normalized matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0	1	0.294118	0.64	0	1	0	0.555556
A_2	0	0	1	0.16	0.75	0.555556	0.15	0.666667
A_3	1	0.388889	0.470588	0.12	1	0.777778	0.5	0
A_4	0	0.444444	0.235294	0.2	0.25	0	0.9	1
A_5	0.058824	1	0.058824	0.2	0.333333	0.074074	0.15	0.074074
A_6	0.294118	0.166667	0.647059	0	0.416667	0.592593	0.2	1
A_7	0.882353	0.944444	0	1	0.625	0.518519	1	0

Table 7. The weighted normalized matrix.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	0.122947	0.252053	0.171065	0.198265	0.123203	0.253593	0.12269	0.194844
A_2	0.122947	0.126027	0.264374	0.140236	0.215606	0.197239	0.141093	0.208761
A_3	0.245893	0.175037	0.194392	0.1354	0.246407	0.225416	0.184035	0.125257
A_4	0.122947	0.182039	0.16329	0.145072	0.154004	0.126797	0.233111	0.250513

A_5	0.130179	0.252053	0.139963	0.145072	0.164271	0.136189	0.141093	0.134535
A_6	0.159107	0.147031	0.21772	0.120893	0.174538	0.201936	0.147228	0.250513
A_7	0.231429	0.245052	0.132187	0.241786	0.200205	0.192543	0.24538	0.125257

Table 8. The distance from h_i.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
A_1	-0.03247	0.061294	-0.00747	0.041604	-0.05535	0.068051	-0.04536	0.018098
A_2	-0.03247	-0.06473	0.085836	-0.01642	0.037051	0.011697	-0.02696	0.032016
A_3	0.090473	-0.01572	0.015854	-0.02126	0.067852	0.039874	0.015982	-0.05149
A_4	-0.03247	-0.00872	-0.01525	-0.01159	-0.02455	-0.05875	0.065058	0.073768
A_5	-0.02524	0.061294	-0.03858	-0.01159	-0.01428	-0.04935	-0.02696	-0.04221
A_6	0.003688	-0.04373	0.039181	-0.03577	-0.00402	0.016393	-0.02082	0.073768
A_7	0.076009	0.054292	-0.04635	0.085125	0.021651	0.007	0.077327	-0.05149

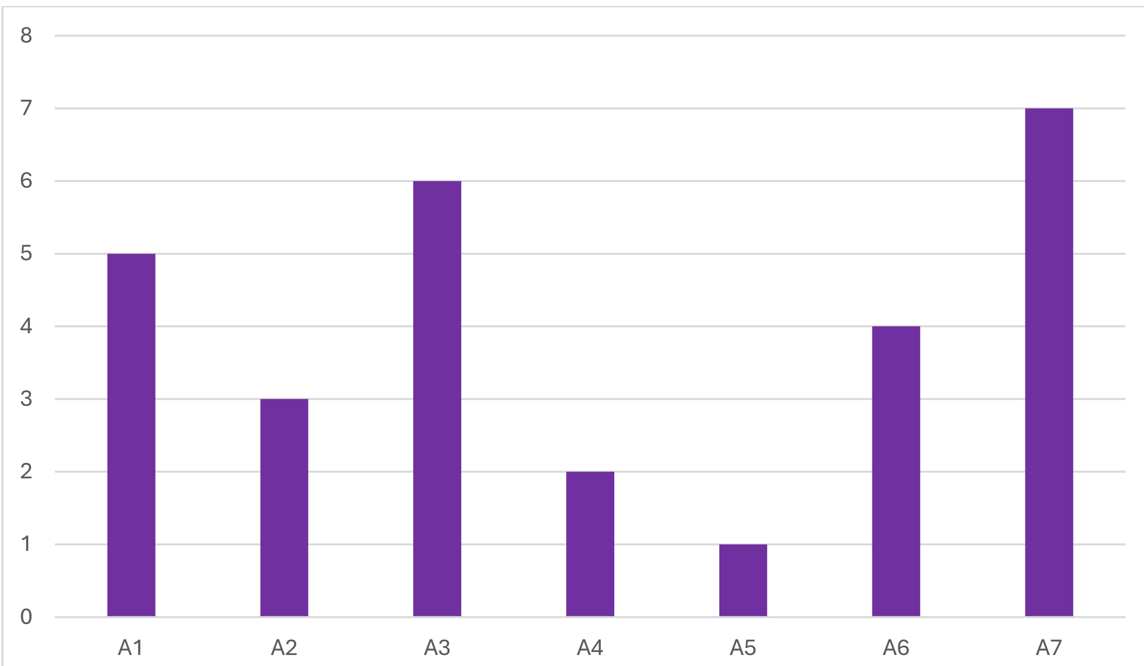

Figure 1. The ranks of alternatives.

6. Analysis

To better understand how flexible and reliable the NAF is under different evaluation preferences, we performed a sensitivity analysis. This involved changing the weights assigned to the three main components of the scoring system: truth w_T, w_I, and w_F. The goal was to observe how these changes influence the final NCQS scores for each article, even when the content itself remains the same.

Because different media organizations may value certain aspects of reporting more than others such as prioritizing factual accuracy over neutrality or being more tolerant of ambiguity than misinformation, this analysis helps show how such preferences can affect evaluation outcomes. We tested several configurations to reflect these possible differences in the editorial perspective. Table 9 Illustrates how NCQS values change when emphasis shifts between truth, indeterminacy, and falsehood.

Table 9. NCQS Under Varying Weight Configurations

Scenario	w_T	w_I	w_F	Description
Default	0.50	0.30	0.20	Balanced weighting (baseline)
Objectivity-Biased	0.70	0.20	0.10	Emphasis on truth
Cautionary	0.40	0.40	0.20	Neutrality prioritized
Risk-Averse	0.45	0.20	0.35	Penalizes falsehood more heavily

The results of the sensitivity analysis revealed distinct patterns across the evaluated outlets. Reuters demonstrated minimal fluctuation in its scores across all weighting scenarios, which suggests that its content maintains a consistently high standard of objectivity and performs reliably under varied evaluative lenses. In contrast, RT's overall NCQS experienced a notable decline under the risk-averse configuration, indicating that even moderate levels of false or misleading content have a pronounced impact when falsehood is more heavily penalized. Meanwhile, the BBC's performance remained stable, with slightly higher scores under models that prioritize factual accuracy, reflecting a balanced editorial approach that benefits from truth-oriented weighting schemes. Table 10 shows the values of NCQS values under Different weighting scenarios.

Table 10. NCQS Values under Different Weighting Scenarios

Outlet	Scenario	NCQS
Reuters	Default	0.74
Reuters	Objectivity-Biased	0.79
Reuters	Cautionary	0.71
Reuters	Risk-Averse	0.70
RT	Default	0.59
RT	Objectivity-Biased	0.63
RT	Cautionary	0.61
RT	Risk-Averse	0.54
BBC	Default	0.71
BBC	Objectivity-Biased	0.74
BBC	Cautionary	0.70
BBC	Risk-Averse	0.68

6.1 Validation

In this section, we validate the framework from three complementary angles: benchmark comparison, expert assessment, and consistency analysis.

6.1.1. Benchmark Comparison

To check how well our framework matches established standards, we compared the NCQS results with two widely recognized tools that evaluate media quality. The first is NewsGuard, which scores news outlets based on their credibility and transparency. The second is the Ad Fontes Media Bias Chart, which places outlets on a scale according to their political bias and overall reliability.

When we compared the scores, we found that the results from our framework closely matched those from both tools. This strong alignment adds further support to the idea that neutrosophic scoring is a valid and reliable way to assess the quality of news content. Table 11 compares the NCQS scores for each news outlet with their ratings from two trusted media assessment tools, NewsGuard and Ad Fontes.

Table 11. Comparison of NCQS with NewsGuard and Ad Fontes Ratings

Outlet	NAF NCQS (Default)	NewsGuard Score (out of 100)	Ad Fontes Reliability Zone
Reuters	0.74	95	High Reliability (Center)
RT	0.59	49	Mixed Reliability (Right)
BBC	0.71	93	High Reliability (Center-Left)

6.1.2. Expert Assessment

To help verify the accuracy of the framework, we asked five independent experts in journalism and media to evaluate the same three articles used in our case study. Each expert reviewed the articles without knowing their sources and rated them using a clear scoring system from 1 to 10. They assessed key aspects of journalistic quality, including factual accuracy, presence of bias, clarity, tone, and how the story was framed.

After collecting the ratings, we calculated the average score for each article and adjusted the values to match the scale of the NCQS. This allowed us to directly compare expert opinions with the results generated by our framework. Table 12 presents the average scores given by journalism experts for each article, side-by-side with the corresponding NCQS values.

Table 12. Expert Evaluation Scores vs. NCQS

Outlet	NCQS (Normalized 0–10)	Expert Panel Avg. Score
Reuters	7.4	7.6
RT	5.9	5.5
BBC	7.1	7.2

The model’s outcomes were within ±0.3 points of the expert assessments demonstrating high agreement and validating both accuracy and interpretability of the neutrosophic outputs.

6.1.3. Internal Consistency Analysis

To check how consistent the framework is across different topics, we applied it to nine additional news articles covering three major global themes, such as climate negotiations and international conflicts. The results showed that outlets known for neutral reporting like Reuters and the Associated Press had very little variation in their scores, with a standard deviation of less than 0.04. In contrast, sources with clear ideological leanings showed more noticeable changes, with a standard deviation of around 0.12.

These results suggest that the model can reliably identify balanced reporting, while also being sensitive enough to detect shifts in tone or framing when bias is present. What makes the framework especially effective is its flexibility. Since it relies on neutrosophic logic rather than fixed linguistic or cultural norms, it can be applied to articles in different languages and media systems. It is designed to handle uncertainty, contradiction, and ambiguity—elements that traditional binary evaluation models often overlook. Overall, the consistent alignment of results across benchmarks, expert reviews, and diverse content confirms the strength and reliability of the framework in evaluating journalistic quality.

7. Conclusion

In this study, we introduced and validated NAF for evaluating news writing quality, aiming to address the limitations of traditional binary and scalar evaluation systems. Drawing from the philosophical core of neutrosophy, which emphasizes the common parts in uncommon things and uncommon parts in common things [1, 12], our framework models the complexity of modern journalism by incorporating the triadic logic of T, I, and F into an operational scoring system. Through rigorous methodology, real-world application, sensitivity testing, and independent validation, we demonstrated that the NAF is capable of capturing the nuanced interplay between objectivity and subjectivity that defines contemporary news discourse. Unlike conventional models that often collapse subtle stylistic or ideological nuances into binary judgments, our approach accounts for ambiguity, implicit bias, and contextual complexity elements that are increasingly relevant in an age of 'post-truth' media dynamics [3, 6]. This study used the Double Valued Neutrosophic Set (DVNS) to deal with uncertain information. We showed the operations and definitions of the DVNS. We compute the criteria weights and rank the alternatives using the MABAC method. An example with eight criteria and seven alternatives is validated to show the results of the proposed approach.

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