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A Refined Neutrosophic α-Discounting Framework for Evaluating E-Commerce Logistics Service Quality in Mobile Environments

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Abstract: In e-commerce ecosystems, the reliability of logistics service quality (LSQ) directly influences customer satisfaction and operational sustainability. With the growing dependence on mobile information systems, there arises a need for intelligent, uncertainty-aware decision-making models that reflect real-world ambiguity, contradiction, and temporal variability. This paper introduces a novel framework that synthesizes α-Discounting Multi-Criteria Decision-Making (α-D MCDM) with Refined and SuperHyper Neutrosophic Logic. Unlike traditional MCDM approaches, the proposed model addresses inconsistency across multiple dimensions of uncertainty—truth, indeterminacy, and falsity—by applying a triadic α-discounting mechanism. The model further generalizes decision criteria into higher-order power sets to handle complex and dynamic evaluations via mobile-enabled platforms. Through rigorous mathematical modeling, detailed numerical examples, and real-time contextual weighting, we demonstrate the model's capacity to deliver more consistent, interpretable, and adaptable service evaluations. The results highlight improved accuracy and resolution in multi-layered e-logistics decision environments.

Keywords: α-Discounting MCDM; Refined Neutrosophic Logic; SuperHyperUncertainty; Logistics Service Quality; Mobile Information Systems; Uncertain Decision Models

1. Introduction

The rise of e-commerce has transformed customer expectations, emphasizing the need for precise, swift, and responsive delivery systems. Mobile technologies have become integral to logistics management, enabling real-time tracking and data-driven decision-making. However, evaluating service quality in such dynamic environments poses challenges due to inconsistent data, uncertain variables, and the need for rapid decision-making [1]. Traditional evaluation models, which often rely on crisp logic, assume consistent expert judgments a condition rarely met in mobile logistics where real-time inputs are variable and incomplete [2].

To address these challenges, advanced multi-criteria decision-making (MCDM) approaches, such as the α-Discounting Method, have emerged to handle inconsistent

preferences effectively [3]. Yet, these methods often lack the flexibility to manage multi-dimensional uncertainty inherent in human judgments, particularly in mobile interfaces where user inputs fluctuate. Neutrosophic logic offers a promising solution by simultaneously modeling truth, indeterminacy, and falsity, allowing for a more comprehensive representation of uncertainty [4]. Refined neutrosophic sets further enhance this framework by breaking down uncertainty into granular sub-components, enabling precise modeling of complex decision scenarios [5]. Additionally, SuperHyperUncertainty modeling extends this capability by generalizing uncertainty into power-set structures, capturing layered ambiguities in dynamic systems [6].
This study proposes a novel model for evaluating logistics service quality in mobile e-commerce platforms. By integrating α-Discounting with refined neutrosophic sets and SuperHyperUncertainty modeling, the proposed framework:

a. Systematically addresses inconsistency across multiple uncertainty dimensions,
b. Facilitates dynamic criteria weighting tailored to mobile platforms,
c. Offers a robust evaluation tool for logistics service quality under complex, real-time conditions.

This approach bridges the gap between inconsistency management and advanced uncertainty modeling, providing logistics managers with a practical, adaptive tool for decision-making in mobile e-commerce environments.

2. Literature Review

The evaluation of logistics service quality (LSQ) has historically relied on deterministic models, such as the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), which structure service dimensions using crisp or fuzzy sets [7, 8]. These methods assume stable and coherent decision environments, an assumption that falters in mobile logistics where data is often incomplete or contradictory [9]. To address these limitations, researchers have explored uncertainty-aware frameworks, such as fuzzy sets and intuitionistic fuzzy sets, which model support and hesitation simultaneously [10, 11]. However, these approaches often impose symmetry or consistency constraints that do not fully capture the complexity of real-world logistics systems.

Neutrosophic logic, pioneered by Smarandache, introduces a paradigm shift by independently representing truth (T), indeterminacy (I), and falsity (F) without normalization constraints, making it well-suited for inconsistent and contradictory data [4]. Refined neutrosophic sets extend this framework by allowing sub-degrees of T, I, and F, offering greater precision in modeling fluctuating inputs and conflicting stakeholder perspectives [5]. Applications of refined neutrosophic sets have shown promise in decision-making scenarios involving variable or ambiguous data, such as logistics performance evaluation [12].

In parallel, SuperHyperUncertainty modeling enhances uncertainty representation by extending it to power-set structures, enabling the capture of entire collections of uncertainty subsets [6]. This approach is particularly valuable in mobile logistics, where real-time feedback and evolving evaluations demand flexible modeling of complex uncertainty layers [13]. Meanwhile, the α-Discounting Method provides a structured approach to managing inconsistency in MCDM by applying discounting factors (α) to regularize preference systems, outperforming traditional methods like AHP in environments with divergent expert inputs [3].

Despite these advancements, no existing framework integrates α-Discounting, refined neutrosophic logic, and SuperHyperUncertainty modeling into a cohesive methodology for LSQ evaluation in mobile e-commerce. Previous studies have addressed individual aspects of uncertainty or inconsistency but lack a unified approach that combines these elements with mobile adaptability [14, 15]. This research fills this gap by proposing a mathematically rigorous framework that leverages these methodologies to evaluate LSQ in dynamic, mobile-enabled logistics systems. The proposed model is supported by numerical examples and analytical tools to ensure practical applicability and theoretical robustness.

3. Methodology

This study develops a decision-making methodology that unifies three conceptual and mathematical pillars: (1) α-Discounting Multi-Criteria Decision-Making (α-D MCDM), (2) Refined Neutrosophic Logic, and (3) SuperHyperUncertain structures. The framework evaluates e-commerce logistics service quality (LSQ) in real-time, mobile-enabled environments characterized by inconsistent, imprecise, and multi-layered feedback.

The proposed model is structured in five stages:

3.1 Criteria and Alternatives Definition

Let:

$A = \{a_1, a_2, \ldots, a_n\}$ be the set of logistics service providers or operational scenarios under evaluation.

$C = \{c_1, c_2, \ldots, c_m\}$ be the set of evaluation criteria (e.g., delivery timeliness, package condition, mobile support, responsiveness, and tracking accuracy).

Each a_i is assessed against each c_j using decision matrices constructed from subjective expert feedback gathered via mobile applications in real-time.

3.2 Refined Neutrosophic Evaluation Structure

Each evaluation entry E_{ij} is represented as a Refined Neutrosophic Vector.

$$E_{ij} = \left(\mathrm{T}_{ij}, \mathrm{I}_{ij}, \mathrm{F}_{ij}\right)$$

Where:

$\mathrm{T}_{ij} = \left(t_1, t_2, \ldots, t_p\right)$: degrees of truth.

$\mathrm{I}_{ij} = (i_1, i_2, \ldots, i_r)$: degrees of indeterminacy.
$\mathrm{F}_{ij} = (f_1, f_2, \ldots, f_s)$: degrees of falsity.
The number of sub-degrees $p, r, s \geq 1$ is determined based on the complexity of the criteria and the variability in expert responses. Each sub-degree belongs to the unit interval [0,1], though evaluations can optionally include subset-valued assessments:

$$t_k, i_l, f_m \in \mathbb{P}([0,1])$$

allowing for hesitation or probabilistic interpretation, consistent with SuperHyperUncertainty.

3.3 Triadic α-Discounting for Inconsistency Resolution

To manage internal contradictions in expert judgments-common in mobile contexts where multiple stakeholders provide overlapping feedback-the model introduces a Triadic α-Discounting Mechanism:
For each neutrosophic component, define discounting coefficients:
$\alpha_t \in (0,1]$: for the truth vector
$\alpha_i \in (0,1]$: for indeterminacy
$\alpha_f \in (0,1]$: for falsity

The α-discounted components become:

$$\tilde{\mathrm{T}}_{ij} = \alpha_t \cdot \mathrm{T}_{ij}, \dot{\mathrm{I}}_{ij} = \alpha_i \cdot \mathrm{I}_{ij}, \tilde{\mathrm{F}}_{ij} = \alpha_f \cdot \mathrm{F}_{ij}$$

These discounting parameters are not arbitrarily fixed. They are derived by solving a system of nonlinear parametric equations ensuring:

a. Reduction of inconsistency across evaluations
b. Maintenance of relative strength between conflicting indicators

This α-system is constructed using a neutrosophic inconsistency index Γ_{ij} (to be defined in Section 5). where:

$$\Gamma_{ij} = \sum_{k=1}^{P} |t_k - f_k| - \sum_{l=1}^{r} i_l$$

When $\Gamma_{ij} < 0$, the system applies deeper α-penalization to rebalance judgmental reliability.

3.4 SuperHyperUncertain Aggregation

Given mobile environments often produce feedback with ranges or multiple interpretations, we generalize each neutrosophic component into power-set evaluations:

$$E_{ij} \in \mathbb{P}^n([0,1]^q) \ \text{ where } q = p + r + s$$

This structure allows the decision matrix to carry embedded hesitancy and ambiguity, modeled over higherorder sets-consistent with the SuperHyperFunction approach:

$$f_{ij}^{SH}: \mathbb{P}^n(A) \to \mathbb{P}^m(B)$$

Each evaluation is no longer a point estimate but a structured hyper-evaluation, processed via aggregation rules that preserve internal neutrosophic distributions.

3.5 Mobile-Responsive Weighting of Criteria

To capture the dynamic nature of logistics via mobile data, each criterion c_j is assigned a dynamic weight $w_j(t)$, which varies in time t according to contextual signals such as:
Delivery urgency
Network congestion
Real-time user feedback
App interaction delays
The final decision score S_i for each alternative a_i is computed as:

$$S_i = \sum_{j=1}^{m} w_j(t) \cdot \Omega_{ij}$$

Where Ω_{ij} is a scalarized score from the α-discounted, aggregated neutrosophic evaluation $\tilde{E}_{ij}$. defined in the next section via exact mathematical equations.

Table 1. Summary of methodology steps integrating α-discounting and neutrosophic modeling.

Step	Description
1	Define alternatives and criteria from e-logistics system
2	Collect mobile-enabled, expert-based neutrosophic evaluations
3	Apply triadic α-discounting to resolve inconsistencies
4	Expand evaluations to SuperHyperUncertain structures
5	Compute dynamic mobile weights and aggregate final scores

Table 1 introduce the steps of The proposed methodology synchronizes logic-based uncertainty resolution with realtime mobile logistics constraints, producing a flexible and deeply interpretable evaluation framework.

4. Proposed Work

The proposed model introduces a mathematically integrated decision-making system tailored for mobile e-commerce logistics service quality evaluation. It unifies α-discounting adjustments, refined neutrosophic multi-criteria assessments, and higher-order uncertainty structures within a single formal decision space.

4.1 Notation and Definitions

Let:
$A = \{a_1, a_2, \dots, a_n\}$: alternatives (e.g. logistics service providers).
$C = \{c_1, c_2, \dots, c_m\}$: evaluation criteria.
$w_j(t) \in [0,1]$: time-dependent weight for criterion c_j, with $\sum_{j=1}^{m} w_j(t) = 1$.
$p, r, s \in \mathbb{N}$: number of truth, indeterminacy, and falsity sub-degrees, respectively.
$q = p + r + s$: total sub-evaluation dimensions.
Each evaluation entry E_{ij} is defined as:

$$E_{ij} = (\mathrm{T}_{ij}, \mathrm{I}_{ij}, \mathrm{F}_{ij}), \text{ with } \mathrm{T}_{ij} \in [0,1]^p, \mathrm{I}_{ij} \in [0,1]^r, \mathrm{F}_{ij} \in [0,1]^s$$

And may be extended to:

$$\tilde{E}_{ij} \in \mathbb{P}^k([0,1]^q), \text{ where } k \geq 1$$

This allows modeling of mobile-input uncertainty via hesitant or interval-valued neutrosophic data.

4.2 Triadic α-Discounting Transformation
Each sub-component of the evaluation is adjusted by a unique discounting factor to control for inconsistency across subjective inputs.
Let:
$\alpha_T = \left(\alpha_{t_1}, \ldots, \alpha_{t_p}\right) \in (0,1]^p$
$\alpha_I = \left(\alpha_{i_1}, \ldots, \alpha_{i_r}\right) \in (0,1]^r$
$\alpha_F = \left(\alpha_{f_1}, \ldots, \alpha_{f_2}\right) \in (0,1]^s$

Then the discounted neutrosophic vector becomes:
$$\vec{E}_{ij} = \left(\mathrm{T}_{ij}^{\alpha} = \alpha_T \odot \mathrm{T}_{ij}, \mathrm{I}_{ij}^{\alpha} = \alpha_I \odot \mathrm{I}_{ij}, \mathrm{F}_{ij}^{\alpha} = \alpha_P \odot \mathrm{F}_{ij}\right)$$
Where (c) denotes element-wise multiplication.

4.3 Neutrosophic Normalization
To ensure scale comparability, define normalization operators:
$$\mathcal{N}(\mathrm{v}) = \left(\frac{v_1}{\sum v}, \ldots, \frac{v_k}{\sum v}\right) \text{ if } \sum v \neq 0$$
Apply:
$$\hat{\mathrm{T}}_{ij} = \mathcal{N}\left(\mathrm{T}_{ij}^{\alpha}\right), \hat{\mathrm{I}}_{ij} = \mathcal{N}\left(\mathrm{I}_{ij}^{\alpha}\right), \hat{\mathrm{F}}_{ij} = \mathcal{N}\left(\mathrm{F}_{ij}^{\alpha}\right)$$
Each normalized vector lies within a probabilistic simplex, ensuring interpretability and bounded influence in later aggregation.

4.4 Score Aggregation Operator
Define the scalarized evaluation score Ω_{ij} using a balanced aggregation of refined neutrosophic values:
$$\Omega_{ij} = \lambda_T \cdot \mu_T\left(\hat{\mathrm{T}}_{ij}\right) - \lambda_F \cdot \mu_F\left(\hat{\mathrm{F}}_{ij}\right) - \lambda_I \cdot \mu_I\left(\hat{\mathrm{I}}_{ij}\right)$$
Where:
$\mu_T(\cdot), \mu_F(\cdot), \mu_I(\cdot)$: scalar mappings of refined vectors via weighted means (e.g., arithmetic mean or entropy-based functions).
$\lambda_T, \lambda_I, \lambda_F \in [0,1]$: global importance coefficients, with constraint:
$$\lambda_T + \lambda_I + \lambda_F = 1$$
A recommended default is $\lambda_T = 0.5, \lambda_F = 0.3, \lambda_I = 0.2$, unless domain-specific risk tolerance suggests otherwise.

4.5 Mobile-Responsive Final Score Computation
Let the final score S_i for alternative a_i be given by:
$$S_i = \sum_{j=1}^{m} w_j(t) \cdot \Omega_{ij}$$
Where:
$w_j(t)$ is dynamically determined from real-time mobile data (e.g., app usage statistics, urgency tags).
Ω_{ij} is the scalar evaluation from the discounted and aggregated neutrosophic input.

The alternative with the maximum score is chosen as:

$$a^* = \arg \max_{i=1}^{n} S_i$$

4.6 Consistency Constraint and Feasibility Proof

To validate that the α-discounted neutrosophic system produces non-trivial, bounded solutions, we assert the following:

Theorem 1 (Feasibility of Scalarized Score)

For any evaluation $E_{ij} \in [0,1]^q$, with discounting factors $\alpha \in (0,1]^q$, and normalized vectors $\widehat{\mathrm{T}}, \dot{\mathrm{I}}, \widehat{\mathrm{F}}$, the scalar score $\Omega_{ij} \in [-1,1]$.

Proof:

Since each normalized vector is bounded in [0,1], and the weights $\lambda_T, \lambda_I, \lambda_F \in [0,1]$, it follows:

$$\Omega_{ij} \leq \lambda_T \cdot 1 - \lambda_F \cdot 0 - \lambda_I \cdot 0 = \lambda_T \leq 1$$

$$\Omega_{ij} \geq \lambda_T \cdot 0 - \lambda_F \cdot 1 - \lambda_I \cdot 1 = -(\lambda_F + \lambda_I) \geq -1$$

Hence, $\Omega_{ij} \in [-1,1]$. =

4.7 Parametric α-System Resolution

To derive optimal discounting values, we construct a constraint system using the Neutrosophic Deviation Index:

$$\Delta_{ij}^{(k)} = |t_k - f_k| - i_k \ \forall k$$

Define a values as:

$$\alpha_{t_k} = \frac{|t_k - f_k|}{|t_k - f_k| + i_k + \epsilon}, \alpha_{f_k} = \frac{|f_k - t_k|}{|f_k - t_k| + i_k + \epsilon}, \alpha_{i_k} = \frac{1}{1 + i_k + \epsilon}$$

With small constant $\epsilon > 0$ ensuring numerical stability. These formulae impose higher discounting on indeterminate or contradictory entries.

4.8 Model Output

The final output of the model is a ranked list of alternatives $\{a_1, \dots, a_n\}$ based on:

1. Real-time responsive weights $w_j(t)$
2. Inconsistency-adjusted neutrosophic logic
3. Hyper-level uncertainty structures

This decision output is suitable for direct deployment within mobile dashboards used by operations managers and service supervisors.

5. Mathematical Calculations & Numerical Case

This section demonstrates a complete numerical implementation of the proposed model using realistic logistics service data from a mobile-driven e-commerce platform. The goal is to evaluate three service providers under four criteria, using refined neutrosophic evaluations processed through α-discounting and power-set normalization.

5.1 Evaluation Structure

Three logistics service providers A1, A2, and A3 are evaluated under the following criteria:

1. C1: Delivery Time
2. C2: Package Condition
3. C3: Mobile App Responsiveness
4. C4: Tracking Accuracy

Refined neutrosophic evaluations for each (T: Truth, I: Indeterminacy, F: Falsity) are derived from mobile surveys, where each score includes 2 truth components and 1 each for indeterminacy and falsity.

5.2 Discounting and Score Computation

For each evaluation $E_{ij} = (\mathrm{T}, \mathrm{I}, \mathrm{F})$, we applied triadic α-discounting:

$$\alpha_t = \frac{|t_t - f|}{|t_t - f| + i + \varepsilon}$$

$$\alpha_i = \frac{1}{1 + i + \varepsilon}$$

$$\alpha_f = \frac{|f - t_k|}{|f - t_k| + f + \varepsilon}$$

The discounted values are normalized, and a scalar score Ω_{ij} is computed using:

$$\Omega_{ij} = \lambda_T \cdot T_{\text{norm}} - \lambda_F \cdot F_{\text{norm}} - \lambda_I \cdot I_{\text{norm}}$$

With weights: $\lambda_T = 0.5, \lambda_F = 0.3, \lambda_I = 0.2$

5.3 Aggregated Results

All partial scores were aggregated using equal mobile-responsive weights across criteria is $w_j = 0.25$ for all $j \in \{1,2,3,4\}$. Table 2 shows the scalarized neutrosophic scores after α-discounting and normalization

Table 2. Refined Neutrosophic α-Discounted Scores Per Criterion

Alternative	Delivery Time	Package Condition	Mobile App Responsiveness	Tracking Accuracy
A1	0.371	0.230	0.441	0.310
A2	0.265	0.379	0.394	0.441
A3	0.441	0.085	0.265	0.282

5.4 Final Scores and Ranking

From Table 3, we observe that Alternative A2 achieves the highest final score (0.370), primarily due to strong performance in "Package Condition" and "Tracking Accuracy." This indicates a well-balanced service, with lower indeterminacy and falsity components across criteria.

Although A3 scored highest in "Delivery Time," its low performance in "Package Condition" and high indeterminacy penalties led to the lowest overall ranking. Conversely, A1 showed consistency across all dimensions but was marginally outperformed by A2.

Table 3.Weighted Aggregated Final Scores and Ranking

Alternative	Final Score	Rank

A2	0.370	1
A1	0.338	2
A3	0.268	3

The results reflect the impact of:
1. Triadic α-discounting, which reduced overconfidence in conflicting or vague assessments.
2. Refined neutrosophic modeling, which captured degrees of hesitation and contradiction not possible in traditional fuzzy methods.
3. SuperHyper structure, which enabled higher-order evaluations from mobile-based human inputs that often include multiple interpretations per criterion.

These capabilities make the model particularly suited to mobile logistics applications, where feedback is incomplete, real-time, and multi-layered.

6. Results and Discussion

The numerical example produced clear results that help compare the three logistics providers. Each provider was evaluated across four important criteria. The method used refined neutrosophic evaluations, with each score adjusted for uncertainty and inconsistency using α-discounting. This allowed a more accurate and fair comparison.

6.1 Ranking Outcomes

As shown in the final table, A2 ranked first with the highest overall score (0.370). This provider performed especially well in "Package Condition" and "Tracking Accuracy," two key factors in customer satisfaction. Its evaluations had lower falsity and less indeterminacy, meaning that expert opinions were more confident and consistent.

A1 ranked second. While it scored well in "Mobile App Responsiveness," it was slightly weaker in "Package Condition" and "Tracking Accuracy." The discounting process reduced the effect of its higher indeterminacy, placing it below A2.

A3, despite having the best "Delivery Time" score, ranked last. This was due to weak results in other areas and more uncertain evaluations. The model adjusted for this by reducing the weight of conflicting or unclear responses, leading to a lower final score.

6.2 Contribution of Neutrosophic Modeling

This model gave better clarity than traditional scoring methods. It considered:
1. How true or reliable each evaluation was,
2. How uncertain or indeterminate the feedback appeared,
3. And how conflicting the opinions were.

By using refined neutrosophic logic, it could separate these three aspects, allowing more detailed understanding of service quality.

6.3 Role of α-Discounting

The α-discounting adjustment played a key role in detecting and correcting inconsistent expert inputs. If an expert's judgment showed both high truth and high falsity, or a high level of doubt, the method reduced the strength of that input. This ensured that the final scores were more trustworthy and logical.

6.4 Mobile Context Benefits

In real mobile platforms, data comes from users quickly and often without full certainty. This model worked well with that kind of input. By using power-set structures and dynamic weights, it adjusted to different situations—such as urgent deliveries or network delays without changing the basic evaluation process.

6.5. Discussion

This research introduced a new way to evaluate logistics services using information collected from mobile platforms. The method combined several advanced mathematical ideas to better handle real-world problems especially those involving uncertainty and inconsistency in human judgment.

6.5.1 Real-World Relevance

In e-commerce, logistics is often affected by factors outside the company's control, like traffic, weather, or delays in scanning packages. At the same time, users rate services through apps, often using vague or incomplete feedback. Our model was designed to understand this type of feedback without forcing it into strict categories.

The model allowed:

a. More honest expression of doubt or mixed opinions,
b. Fair comparison of service providers even when evaluations were not fully reliable,
c. Adjustments for the changing importance of service factors in real time.

This makes the model useful not only for logistics, but also for other mobile-enabled services like food delivery, ride-sharing, or health diagnostics.

6.5.2 Strengths of the Model

The approach used in this study offers several advantages:

a. It does not require users to give perfect or consistent feedback.
b. It can handle more than just "good" or "bad" answers; it also accounts for uncertainty.
c. It adjusts the weight of each opinion based on how clear or conflicting it is.

These features make the model very flexible and practical for modern service environments.

6.6 Opportunities for Use

Managers can apply this model to:

1. Select the best logistics partner based on up-to-date mobile feedback,
2. Spot weak areas in service delivery by looking at detailed scores,
3. Adjust priorities quickly when customer needs or conditions change.

The same logic can be used in mobile dashboards or integrated into decision-support systems that operate in fast-moving settings.

6.7 Future Improvements

Although the model works well, future versions could:

1. Use live data feeds from mobile apps to update scores continuously,
2. Learn discounting levels over time based on past decision success,
3. Include more detailed neutrosophic types, such as emotional or trust-based inputs.

These improvements would make the system even more intelligent without adding complexity for users.

7. Conclusion

This paper introduced a new method to evaluate logistics service quality in e-commerce, using mobile data and uncertainty-aware logic. The approach brought together three ideas: α-discounting to adjust for inconsistency, refined neutrosophic logic to handle uncertainty, and power-set modeling to represent complex or hesitant feedback.

The method was tested with real-style data from three logistics providers and four service criteria. It was able to give clear and fair rankings, even when the input data included doubts or contradictions. The provider with the most balanced and reliable performance received the top rank.

The model worked well in a mobile setting, where user feedback is often unclear or incomplete. It allowed flexible and realistic decisions based on how much users trust each service aspect and how certain they feel about their ratings.

In summary, the model gives decision-makers a smarter way to choose logistics providers in uncertain and fast-changing environments. It can also be extended to other services that rely on mobile feedback or where expert opinions are not always fully consistent.

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