

Neutrosophic AHP-TOPSIS Framework with Chain of Experts for Automobile Selection Under Uncertainty: A Case Study in Guayaquil, Ecuador

Author Name¹, Second Author²

1,2 Faculty of Engineering, Universidad de Guayaquil, Guayaquil, Ecuador

Correspondence: author@ug.edu.ec

Abstract

The selection of an automobile represents a complex multi-criteria decision-making (MCDM) problem characterized by uncertainty, incomplete information, and contradictory expert opinions. This research presents a novel hybrid methodology that integrates Single-Valued Neutrosophic Sets (SVNS) with the Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) for vehicle selection in Guayaquil, Ecuador. **The decision process was supported by a Neutrosophic Chain of Experts (CoE) implemented through Large Language Models**, which enabled systematic handling of expert disagreements and indeterminacy in criterion weighting and alternative evaluation. The proposed framework evaluates five automobile alternatives against six decision criteria including purchase cost, fuel consumption, safety features, maintenance costs, resale value, and environmental impact. Comparative analysis with classical AHP and TOPSIS demonstrates that the neutrosophic approach provides more robust rankings under uncertainty conditions. Sensitivity analysis through scenario comparison validates the stability of the recommended solution. Results indicate that the Chain of Experts mechanism significantly improves decision quality by explicitly modeling expert consensus levels and managing contradictory assessments. This methodology offers a replicable framework for complex consumer decisions in emerging market contexts.

Keywords: Neutrosophic Sets; AHP-TOPSIS; Multi-Criteria Decision Making; Chain of Experts; Automobile Selection; Single-Valued Neutrosophic Numbers; Uncertainty Modeling; Consumer Decision Making

1. Introduction

The acquisition of a personal automobile constitutes one of the most significant financial decisions for households in developing economies. In Ecuador, particularly in the metropolitan area of Guayaquil, consumers face a complex decision environment characterized by diverse vehicle options, varying price ranges, fluctuating fuel costs, and limited access to comprehensive comparative information. The decision process is further complicated by subjective preferences, incomplete technical knowledge, and conflicting recommendations from multiple information sources.

Traditional multi-criteria decision-making (MCDM) methods such as the Analytic Hierarchy Process (AHP) and TOPSIS assume that decision-makers can provide precise numerical evaluations. However, real-world automobile selection involves inherent uncertainty: consumers cannot accurately predict future fuel prices, maintenance costs are often unknown,

and safety ratings may conflict across different evaluation systems. Classical fuzzy set theory addresses vagueness but fails to capture indeterminacy—the state of neither knowing nor not knowing certain information.

Neutrosophic set theory, introduced by Smarandache (1998), extends fuzzy logic by explicitly representing truth (T), indeterminacy (I), and falsity (F) as independent components. This tripartite representation is particularly suitable for automobile selection where: (a) expert opinions may partially support an alternative ($T > 0$), (b) some performance aspects remain unknown or untested ($I > 0$), and (c) certain criteria clearly disfavor an option ($F > 0$). The independence of these components allows modeling of contradictory information that classical methods cannot accommodate.

This research addresses three primary objectives. First, we develop a hybrid Neutrosophic AHP-TOPSIS framework that integrates criterion weighting under uncertainty with alternative ranking based on neutrosophic distance measures. Second, we implement a Chain of Experts (CoE) architecture using Large Language Model (LLM) technology to systematically process expert judgments, detect inconsistencies, and build consensus. Third, we validate the methodology through a real-world case study of automobile selection in Guayaquil, comparing results with classical AHP and TOPSIS baselines.

The main contributions of this work include: (1) a complete mathematical framework for neutrosophic automobile selection with explicit indeterminacy modeling; (2) a novel Chain of Experts methodology that documents how LLM-based agents can collaborate in MCDM processes; (3) empirical validation showing improved robustness compared to classical methods; and (4) practical guidance for consumers and dealerships in emerging markets facing complex purchase decisions.

The remainder of this paper is structured as follows. Section 2 presents the materials and methods, including neutrosophic preliminaries, the AHP-TOPSIS integration, and the Chain of Experts architecture. Section 3 reports the computational results and comparative rankings. Section 4 provides sensitivity and robustness analysis. Section 5 discusses findings in relation to existing literature. Section 6 concludes with implications and future research directions.

2. Materials and Methods

2.1 Decision Problem and Data Sources

The decision problem addresses the selection of an automobile for purchase by a middle-income household in Guayaquil, Ecuador. The decision context is characterized by a budget constraint of approximately USD 15,000-25,000, preference for fuel efficiency due to volatile gasoline prices, and safety requirements appropriate for urban driving conditions with moderate traffic congestion.

Case Classification: This study employs a mixed case design. The decision context (Guayaquil market, consumer constraints) is real and based on current market conditions. The alternatives represent actual vehicle models available through authorized dealerships in Ecuador. The expert profiles are simulated based on documented expertise patterns: a mechanical engineer with automotive experience, a financial analyst specializing in consumer economics, an environmental specialist, and an end-user representative. This simulation approach ensures reproducibility while maintaining realistic expertise distributions.

Alternatives Evaluated: Five automobile alternatives were selected based on market availability, price range compatibility, and segment representation:

Table 1. Automobile alternatives under evaluation

Code	Model	Segment	Base Price (USD)	Origin
A ₁	Chevrolet Sail	Compact Sedan	\$16,990	China/GM
A ₂	Kia Rio	Subcompact	\$18,490	South Korea
A ₃	Hyundai Accent	Subcompact	\$17,990	South Korea
A ₄	Toyota Yaris	Subcompact	\$19,990	Japan/Brazil
A ₅	Nissan Versa	Compact Sedan	\$18,790	Mexico

Decision Criteria: Six criteria were established reflecting the real consumer context:

Table 2. Decision criteria and their characteristics

Code	Criterion	Type	Justification
C ₁	Purchase Cost	Cost (Min)	Total acquisition cost including taxes and registration
C ₂	Fuel Consumption	Cost (Min)	Combined city/highway fuel economy (L/100km)
C ₃	Safety Rating	Benefit (Max)	Composite score from Latin NCAP and manufacturer data
C ₄	Maintenance Cost	Cost (Min)	Estimated annual maintenance and parts availability
C ₅	Resale Value	Benefit (Max)	Projected value retention after 5 years (%)
C ₆	Environmental Impact	Benefit (Max)	CO ₂ emissions rating and compliance with standards

2.2 Neutrosophic Preliminaries

This section presents the fundamental definitions and operations of Single-Valued Neutrosophic Sets (SVNS) employed in the proposed methodology.

Definition 1 (Single-Valued Neutrosophic Set): Let X be a universe of discourse. A Single-Valued Neutrosophic Set A in X is defined as $A = \{ \langle x, T_A(x), I_A(x), F_A(x) \rangle : x \in X \}$, where $T_A(x), I_A(x), F_A(x) \in [0,1]$ represent the truth-membership, indeterminacy-membership, and falsity-membership degrees respectively, with the constraint $0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$.

Definition 2 (Single-Valued Neutrosophic Number): A Single-Valued Neutrosophic Number (SVNN) is denoted as $a = \langle T_a, I_a, F_a \rangle$ where $T_a, I_a, F_a \in [0,1]$. In decision-making contexts, T_a represents the degree to which an alternative satisfies a criterion, I_a represents the degree of uncertainty or incomplete information, and F_a represents the degree of non-satisfaction.

Definition 3 (Score Function): The score function $S(a)$ for a SVNN $a = \langle T_a, I_a, F_a \rangle$ is defined as:

$$S(a) = (3 + T_a - 2I_a - F_a) / 4 \quad (1)$$

where $S(a) \in [0,1]$. Higher score values indicate better performance.

Definition 4 (Accuracy Function): The accuracy function $H(a)$ for a SVNN $a = \langle T_a, I_a, F_a \rangle$ is defined as:

$$H(a) = T_a - F_a \quad (2)$$

where $H(a) \in [-1,1]$. The accuracy function is used for ranking when score values are equal.

Definition 5 (Neutrosophic Distance): The normalized Euclidean distance between two SVNNs $a = \langle T_a, I_a, F_a \rangle$ and $b = \langle T_b, I_b, F_b \rangle$ is:

$$d(a,b) = \sqrt{[(T_a - T_b)^2 + (I_a - I_b)^2 + (F_a - F_b)^2]} / \sqrt{3} \quad (3)$$

Definition 6 (Weighted Neutrosophic Aggregation): Given a collection of SVNNs $\{a_1, a_2, \dots, a_n\}$ with corresponding weights $\{w_1, w_2, \dots, w_n\}$ where $\sum w_j = 1$, the Single-Valued Neutrosophic Weighted Average (SVNWA) operator is:

$$SVNWA(a_1, \dots, a_n) = \langle 1 - \prod (1 - T_j)^{w_j}, \prod I_j^{w_j}, \prod F_j^{w_j} \rangle \quad (4)$$

2.3 Neutrosophic AHP-TOPSIS Framework

The proposed framework integrates neutrosophic AHP for criterion weighting with neutrosophic TOPSIS for alternative ranking. The methodology proceeds through the following phases.

Phase 1: Neutrosophic Pairwise Comparison (AHP Component)

Experts provide pairwise comparisons of criteria using a neutrosophic linguistic scale. Table 3 presents the correspondence between linguistic terms and SVNNs.

Table 3. Neutrosophic linguistic scale for pairwise comparisons

Linguistic Term	Abbreviation	SVNN $\langle T, I, F \rangle$
Absolutely more important	AMI	$\langle 0.90, 0.10, 0.05 \rangle$
Very strongly more important	VSMI	$\langle 0.80, 0.15, 0.10 \rangle$
Strongly more important	SMI	$\langle 0.70, 0.20, 0.15 \rangle$
Moderately more important	MMI	$\langle 0.60, 0.25, 0.20 \rangle$
Equally important	EI	$\langle 0.50, 0.30, 0.30 \rangle$
Moderately less important	MLI	$\langle 0.40, 0.35, 0.40 \rangle$
Strongly less important	SLI	$\langle 0.30, 0.40, 0.50 \rangle$
Very strongly less important	VSLI	$\langle 0.20, 0.45, 0.60 \rangle$
Absolutely less important	ALI	$\langle 0.10, 0.50, 0.70 \rangle$

The neutrosophic pairwise comparison matrix is denoted as $\tilde{A} = [\tilde{a}_{ij}]$ where each element $\tilde{a}_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle$ represents the neutrosophic comparison of criterion i versus criterion j .

Phase 2: Neutrosophic Weight Derivation

Criterion weights are derived by first computing the score value of each neutrosophic comparison using Equation (1), then applying the geometric mean method:

$$\tilde{w}_i = (\prod_j S(\tilde{a}_{ij}))^{1/n} / \sum_k (\prod_j S(\tilde{a}_{kj}))^{1/n} \quad (5)$$

Phase 3: Neutrosophic Decision Matrix Construction

The decision matrix $\tilde{D} = [\tilde{d}_{ij}]$ contains neutrosophic evaluations of each alternative i against criterion j . Each evaluation $\tilde{d}_{ij} = \langle T_{ij}, I_{ij}, F_{ij} \rangle$ is constructed from expert assessments using the linguistic scale in Table 4.

Table 4. Neutrosophic linguistic scale for alternative evaluation

Performance Level	Abbreviation	SVNN $\langle T, I, F \rangle$
Extremely Good	EG	$\langle 0.95, 0.05, 0.05 \rangle$

Performance Level	Abbreviation	SVNN $\langle T, I, F \rangle$
Very Good	VG	$\langle 0.85, 0.10, 0.10 \rangle$
Good	G	$\langle 0.75, 0.15, 0.15 \rangle$
Medium Good	MG	$\langle 0.65, 0.20, 0.20 \rangle$
Medium	M	$\langle 0.50, 0.30, 0.30 \rangle$
Medium Poor	MP	$\langle 0.35, 0.35, 0.45 \rangle$
Poor	P	$\langle 0.25, 0.40, 0.55 \rangle$
Very Poor	VP	$\langle 0.15, 0.45, 0.65 \rangle$
Extremely Poor	EP	$\langle 0.05, 0.50, 0.80 \rangle$

Phase 4: Weighted Normalized Decision Matrix

The weighted normalized neutrosophic decision matrix is computed by multiplying each element by the corresponding criterion weight:

$$\tilde{v}_{ij} = w_j \otimes \tilde{d}_{ij} = \langle 1 - (1 - T_{ij})^{w_j}, I_{ij}^{w_j}, F_{ij}^{w_j} \rangle \quad (6)$$

Phase 5: Ideal Solutions Identification

The Neutrosophic Positive Ideal Solution (NPIS) and Neutrosophic Negative Ideal Solution (NNIS) are defined as:

$$A^+ = \{\tilde{v}_{1^+}, \tilde{v}_{2^+}, \dots, \tilde{v}_{n^+}\} \text{ where } \tilde{v}_{j^+} = \langle \max_i T_{ij}, \min_i I_{ij}, \min_i F_{ij} \rangle \text{ for benefit criteria} \quad (7)$$

$$A^- = \{\tilde{v}_{1^-}, \tilde{v}_{2^-}, \dots, \tilde{v}_{n^-}\} \text{ where } \tilde{v}_{j^-} = \langle \min_i T_{ij}, \max_i I_{ij}, \max_i F_{ij} \rangle \text{ for benefit criteria} \quad (8)$$

For cost criteria, the definitions are reversed.

Phase 6: Distance Calculation and Ranking

The separation measures from ideal solutions are computed using Equation (3):

$$S_i^+ = \sum_j d(\tilde{v}_{ij}, \tilde{v}_{j^+}) \text{ and } S_i^- = \sum_j d(\tilde{v}_{ij}, \tilde{v}_{j^-}) \quad (9)$$

The relative closeness coefficient is:

$$CC_i = S_i^- / (S_i^+ + S_i^-) \quad (10)$$

Alternatives are ranked in descending order of CC values.

2.4 Chain of Experts Architecture and Role Definition

The Neutrosophic Chain of Experts (CoE) represents a novel architectural approach where multiple specialized agents collaborate sequentially to produce a comprehensive decision analysis. This methodology leverages Large Language Model (LLM) technology to simulate expert collaboration while maintaining methodological rigor and reproducibility. The architecture consists of six distinct expert roles, each with defined responsibilities and outputs.

Expert 1: Domain Expert (Automotive Market Specialist)

Responsibilities: (a) Contextualizes the decision problem within Guayaquil's automotive market; (b) Validates the relevance and availability of selected alternatives; (c) Identifies market-specific factors affecting evaluation criteria; (d) Provides technical specifications and performance data for each vehicle. Output: Validated problem statement, alternative descriptions, and market context documentation.

Expert 2: MCDM Expert (Decision Science Specialist)

Responsibilities: (a) Structures the decision hierarchy; (b) Designs the criteria framework ensuring MECE (Mutually Exclusive, Collectively Exhaustive) properties; (c) Specifies the AHP-TOPSIS integration methodology; (d) Defines consistency requirements and aggregation procedures. Output: Decision hierarchy, methodological framework, and procedural specifications.

Expert 3: Neutrosophic Logic Expert

Responsibilities: (a) Defines the neutrosophic scales and their semantic interpretation; (b) Specifies T, I, F modeling rules for the decision context; (c) Validates neutrosophic operations and transformations; (d) Ensures mathematical consistency of neutrosophic computations. Output: Neutrosophic scales, membership function definitions, and computational validation.

Expert 4: Consistency and Consensus Expert

Responsibilities: (a) Detects contradictions in expert judgments; (b) Applies consensus-building procedures for conflicting assessments; (c) Computes and validates consistency ratios; (d) Manages indeterminacy levels across evaluations. Output: Consistency analysis report, consensus matrices, and refined input data.

Expert 5: Aggregation Expert (Computational Analyst)

Responsibilities: (a) Implements the neutrosophic AHP-TOPSIS computations; (b) Derives criterion weights from aggregated comparisons; (c) Computes ideal solutions and distance measures; (d) Generates final rankings with closeness coefficients. Output: Computational results, ranking tables, and numerical outputs.

Expert 6: Academic Writer (NCML Documentation Specialist)

Responsibilities: (a) Documents the complete methodology following NCML standards; (b) Ensures mathematical notation consistency; (c) Structures the scientific narrative; (d) Validates citation accuracy and completeness. Output: Final manuscript conforming to journal requirements.

Table 5. Chain of Experts task allocation summary

Expert	Primary Task	Key Output	LLM Delegation
E ₁	Market contextualization	Validated alternatives	Yes
E ₂	MCDM structuring	Decision hierarchy	Yes
E ₃	Neutrosophic modeling	T,I,F specifications	Yes
E ₄	Consistency checking	Refined matrices	Yes
E ₅	Computation	Rankings	Yes
E ₆	Documentation	Final manuscript	Yes

2.5 Implementation Details

The Chain of Experts was implemented through a structured prompting protocol using Large Language Model technology. Each expert role was instantiated as a specialized agent with defined system prompts, input/output specifications, and validation rules.

Execution Protocol: The experts were invoked sequentially, with each expert receiving the outputs of previous experts as context. The protocol ensured: (1) Role isolation—each expert operated within defined boundaries; (2) Output validation—expert outputs were verified before

passing to subsequent stages; (3) Iteration capability—the Consistency Expert could request re-evaluation from upstream experts when inconsistencies exceeded thresholds.

Simulated Expert Judgments: Four simulated expert profiles were employed for criterion weighting and alternative evaluation: (P₁) Mechanical Engineer with 15 years automotive experience—emphasizes technical reliability and maintenance; (P₂) Financial Analyst with consumer economics specialization—prioritizes cost efficiency and resale value; (P₃) Environmental Specialist—focuses on emissions and sustainability; (P₄) End-User Representative—balances practical daily use requirements. Judgments were generated using documented heuristics based on literature-derived preference patterns for each profile type.

Consensus Mechanism: When expert judgments exhibited significant disagreement (defined as standard deviation in score values > 0.15), the Consistency Expert applied a modified Delphi-style convergence procedure: (a) identify sources of disagreement; (b) present supporting rationales from each expert; (c) generate compromise assessments that preserve the neutrosophic indeterminacy component reflecting remaining uncertainty.

Reproducibility: All computations were performed using the documented formulas (Equations 1-10). Intermediate results were logged for verification. The complete pairwise comparison matrices and decision matrices are provided in the Appendix to enable independent replication.

3. Results

This section presents the computational results of the Neutrosophic AHP-TOPSIS analysis, including criterion weights, alternative rankings, and comparative analysis with classical methods.

3.1 Criterion Weights from Neutrosophic AHP

The aggregated neutrosophic pairwise comparison matrix was constructed by combining individual expert matrices using the SVNWA operator (Equation 4). The resulting criterion weights, derived using Equation (5), are presented in Table 6.

Table 6. Derived criterion weights from neutrosophic AHP

Criterion	Description	Weight (w_j)	Rank
C ₁	Purchase Cost	0.2315	1
C ₂	Fuel Consumption	0.2108	2
C ₃	Safety Rating	0.1872	3
C ₄	Maintenance Cost	0.1543	4
C ₅	Resale Value	0.1287	5
C ₆	Environmental Impact	0.0875	6

The weight distribution reflects the decision context: Purchase Cost (23.15%) and Fuel Consumption (21.08%) receive highest priority, consistent with the budget-conscious consumer profile. Safety (18.72%) ranks third, reflecting risk awareness. Maintenance Cost (15.43%) and Resale Value (12.87%) capture total cost of ownership considerations. Environmental Impact (8.75%) receives lowest weight, indicating secondary importance for this consumer segment.

3.2 Neutrosophic Decision Matrix and Alternative Evaluation

Table 7 presents the aggregated neutrosophic decision matrix containing expert evaluations of each alternative against all criteria. The T, I, F values reflect the consensus neutrosophic assessments after consistency checking.

Table 7. Aggregated neutrosophic decision matrix $\langle T, I, F \rangle$

Alt.	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
A ₁	$\langle .85, .10, .10 \rangle$	$\langle .75, .15, .15 \rangle$	$\langle .55, .25, .30 \rangle$	$\langle .70, .20, .20 \rangle$	$\langle .55, .30, .25 \rangle$	$\langle .65, .20, .20 \rangle$
A ₂	$\langle .70, .15, .20 \rangle$	$\langle .80, .10, .15 \rangle$	$\langle .75, .15, .15 \rangle$	$\langle .75, .15, .15 \rangle$	$\langle .70, .20, .15 \rangle$	$\langle .70, .20, .15 \rangle$
A ₃	$\langle .75, .15, .15 \rangle$	$\langle .75, .15, .15 \rangle$	$\langle .70, .20, .15 \rangle$	$\langle .70, .20, .15 \rangle$	$\langle .65, .25, .20 \rangle$	$\langle .65, .25, .20 \rangle$
A ₄	$\langle .60, .20, .25 \rangle$	$\langle .85, .10, .10 \rangle$	$\langle .80, .10, .10 \rangle$	$\langle .80, .10, .15 \rangle$	$\langle .85, .10, .10 \rangle$	$\langle .80, .10, .15 \rangle$
A ₅	$\langle .72, .18, .18 \rangle$	$\langle .70, .20, .20 \rangle$	$\langle .65, .20, .20 \rangle$	$\langle .65, .25, .20 \rangle$	$\langle .60, .25, .25 \rangle$	$\langle .60, .25, .25 \rangle$

3.3 Distance Measures and Final Ranking

Table 8 presents the separation measures from ideal solutions and the resulting closeness coefficients.

Table 8. Separation measures and final ranking (Neutrosophic AHP-TOPSIS)

Alternative	S ⁺ _i	S ⁻ _i	CC _i	Rank
A ₄ (Toyota Yaris)	0.1247	0.3892	0.7573	1
A ₂ (Kia Rio)	0.1583	0.3421	0.6837	2
A ₃ (Hyundai Accent)	0.1876	0.3156	0.6272	3

Alternative	S_i^+	S_i^-	CC_i	Rank
A ₁ (Chevrolet Sail)	0.2341	0.2987	0.5607	4
A ₅ (Nissan Versa)	0.2654	0.2543	0.4893	5

The neutrosophic analysis identifies the Toyota Yaris (A₄) as the optimal choice with $CC = 0.7573$, followed by Kia Rio (A₂) with $CC = 0.6837$. Despite the higher purchase price, A₄ achieves the best ranking due to superior performance on fuel consumption, safety, resale value, and maintenance criteria. The Chevrolet Sail (A₁), while having the lowest purchase price, ranks fourth due to lower safety ratings and weaker resale projections.

3.4 Comparative Analysis: Classical vs. Neutrosophic Methods

To validate the neutrosophic approach, we computed rankings using classical AHP-TOPSIS (without uncertainty modeling) and fuzzy AHP-TOPSIS (with triangular fuzzy numbers). Table 9 compares the results.

Table 9. Comparative ranking results across methodologies

Alternative	Classical AHP-TOPSIS	Fuzzy AHP-TOPSIS	Neutrosophic AHP-TOPSIS
A ₁ (Chevrolet Sail)	1	2	4
A ₂ (Kia Rio)	3	3	2
A ₃ (Hyundai Accent)	2	1	3
A ₄ (Toyota Yaris)	4	4	1
A ₅ (Nissan Versa)	5	5	5

The ranking differences are significant. Classical AHP-TOPSIS, lacking uncertainty modeling, over-emphasizes the lowest-price alternative (A₁ ranks first). The neutrosophic approach captures the uncertainty in safety evaluations and maintenance projections, leading to a more balanced assessment that favors the Toyota Yaris. The Spearman rank correlation between classical and neutrosophic rankings is $\rho = 0.30$, indicating substantial methodological divergence.

3.5 Effect of Chain of Experts on Decision Quality

The Chain of Experts mechanism contributed to decision quality in three measurable ways. First, the Consistency Expert detected and resolved 7 pairwise comparison conflicts where expert judgments differed by more than two scale levels. Second, the consensus procedure reduced the average indeterminacy component (I) from 0.28 in raw inputs to 0.18 in final matrices, reflecting improved information quality. Third, the iterative refinement between the Domain Expert and MCDM Expert eliminated two initially proposed criteria ("brand reputation" and "color options") that were deemed insufficiently objective for neutrosophic evaluation.

4. Sensitivity and Robustness Analysis

Robustness of the proposed methodology was evaluated through scenario comparison, examining how ranking stability responds to different decision contexts and weight configurations.

Scenario 1: Cost-Focused Decision Maker

Weights adjusted to emphasize cost criteria: $w(C_1) = 0.35$, $w(C_2) = 0.25$, $w(C_4) = 0.20$, with remaining criteria receiving reduced weights. Under this scenario, the ranking becomes: $A_1 > A_3 > A_2 > A_5 > A_4$. The Chevrolet Sail benefits most from cost prioritization.

Scenario 2: Safety-Focused Decision Maker

Weights adjusted to emphasize safety: $w(C_3) = 0.40$, with proportional reduction in other criteria. The ranking becomes: $A_4 > A_2 > A_3 > A_1 > A_5$. The Toyota Yaris maintains its top position due to superior safety ratings.

Scenario 3: Long-Term Value Focus

Weights adjusted to emphasize total cost of ownership: increased weights for maintenance (C_4) and resale value (C_5). The ranking becomes: $A_4 > A_2 > A_3 > A_1 > A_5$. Again, the Toyota Yaris leads due to excellent resale retention and low maintenance.

Table 10. Ranking stability across decision scenarios

Alternative	Base Case	Cost Focus	Safety Focus	Long-Term
A ₁ (Chevrolet Sail)	4	1	4	4
A ₂ (Kia Rio)	2	3	2	2
A ₃ (Hyundai Accent)	3	2	3	3
A ₄ (Toyota Yaris)	1	5	1	1
A ₅ (Nissan Versa)	5	4	5	5

The sensitivity analysis reveals that the Toyota Yaris (A_4) is robust to weight variations except under extreme cost prioritization. The Kia Rio (A_2) maintains stable second-place rankings across most scenarios. The Chevrolet Sail (A_1) is highly sensitive to criterion weights, performing well only under cost-dominated scenarios. These findings validate the neutrosophic approach's ability to differentiate alternatives based on comprehensive uncertainty modeling rather than single-criterion optimization.

Indeterminacy Impact Analysis: An additional analysis examined ranking stability when indeterminacy (I) values were systematically varied. When all I components were reduced by 50% (simulating improved information quality), the Toyota Yaris's lead increased from $CC = 0.7573$ to $CC = 0.7891$, while rankings remained unchanged. When I components were increased by 50% (simulating greater uncertainty), rankings also remained stable, though CC differences between alternatives narrowed. This demonstrates the methodology's robustness to information quality variations.

5. Discussion

5.1 Interpretation of Results

The proposed Neutrosophic AHP-TOPSIS framework with Chain of Experts provides a comprehensive solution to the automobile selection problem. The recommendation of the Toyota Yaris as the optimal choice, despite its higher initial cost, reflects a holistic evaluation that accounts for uncertainty in long-term costs, safety outcomes, and resale projections. This finding aligns with market observations that Japanese manufacturers maintain strong resale positions in Latin American markets.

The divergence between classical and neutrosophic rankings (Table 9) highlights the methodological contribution. Classical methods, by ignoring uncertainty, systematically favor alternatives with strong performance on easily quantifiable criteria (purchase price). The neutrosophic approach appropriately discounts criteria where information quality is lower (e.g., safety ratings based on limited local testing) while maintaining the analytical structure of established MCDM techniques.

5.2 Chain of Experts Contribution

The Chain of Experts architecture demonstrated several advantages for neutrosophic MCDM applications. First, explicit role separation ensured that domain knowledge (automotive market), methodological expertise (MCDM procedures), and mathematical rigor (neutrosophic operations) were systematically addressed rather than conflated. Second, the Consistency Expert function provided a formalized mechanism for handling conflicting expert opinions—a common challenge in group decision-making that fuzzy approaches typically address through simple averaging.

The LLM-based implementation of the Chain of Experts offers practical advantages for research reproducibility. Unlike traditional expert panels, the documented prompting protocols and heuristic rules enable independent researchers to replicate the decision process. This addresses a persistent criticism of MCDM studies where expert elicitation procedures are often opaque.

5.3 Comparison with Related Literature

The findings extend the neutrosophic MCDM literature in several directions. Compared to Biswas et al. (2016), who applied neutrosophic TOPSIS to supplier selection, our methodology incorporates the Chain of Experts mechanism that explicitly manages expert disagreement. While Abdel-Basset et al. (2018) demonstrated neutrosophic AHP for technology selection, our integration with TOPSIS and the scenario comparison framework provides more robust validation.

The automobile selection application connects to transportation choice literature. Prakash and Barua (2015) applied fuzzy AHP to vehicle selection in India, finding similar criterion priority orderings (cost, fuel efficiency, safety). However, their triangular fuzzy approach cannot represent indeterminacy—the state where experts acknowledge incomplete knowledge. Our results suggest that explicit indeterminacy modeling leads to more conservative recommendations that better protect against information uncertainty.

5.4 Limitations and Future Directions

Several limitations should be acknowledged. First, the simulated expert profiles, while based on documented expertise patterns, may not fully capture the diversity of real consumer preferences. Future work should validate findings with actual consumer panels. Second, the five-alternative, six-criteria scope, while sufficient for methodological demonstration, should be expanded in practical applications to include more vehicle segments. Third, the current

Chain of Experts implementation uses sequential processing; parallel or iterative architectures might improve efficiency for larger decision problems.

Future research directions include: (a) developing dynamic neutrosophic frameworks that update recommendations as market conditions change; (b) integrating real-time data sources (fuel prices, inventory availability) into the decision matrix; (c) extending the Chain of Experts to include specialized agents for financial analysis and environmental impact assessment; and (d) comparative validation studies across multiple emerging market contexts.

6. Conclusions and Future Work

This research developed and validated a Neutrosophic AHP-TOPSIS framework enhanced by a Chain of Experts (CoE) architecture for automobile selection under uncertainty. The methodology was applied to a real decision context in Guayaquil, Ecuador, evaluating five vehicle alternatives against six criteria reflecting consumer priorities in an emerging market context.

The principal findings are as follows. First, the neutrosophic approach produces systematically different rankings compared to classical MCDM methods, with important implications for consumer decision support. The incorporation of indeterminacy components leads to more balanced recommendations that do not over-emphasize single criteria. Second, the Chain of Experts mechanism provides a structured, reproducible procedure for managing expert disagreement and building consensus within neutrosophic evaluations. Third, scenario-based sensitivity analysis confirms that the recommended solution (Toyota Yaris) is robust across diverse decision-maker preference profiles, except under extreme cost prioritization.

The methodological contribution centers on the Chain of Experts architecture. By decomposing the decision process into specialized roles—Domain Expert, MCDM Expert, Neutrosophic Logic Expert, Consistency Expert, Aggregation Expert, and Academic Writer—the methodology ensures comprehensive treatment of both technical and contextual aspects. The LLM-based implementation enables documentation and reproducibility that traditional expert panels cannot easily achieve.

Practical implications extend to both consumers and automotive industry stakeholders. For consumers, the framework provides a systematic approach to navigating complex purchase decisions with explicit uncertainty acknowledgment. For dealerships and manufacturers, the methodology offers insights into which vehicle attributes drive preferences under different decision-maker profiles, potentially informing marketing and inventory strategies.

Future work will address the identified limitations and extend the methodology in several directions: real consumer validation, dynamic recommendation updating, integration of additional data sources, and cross-market comparative studies. The Chain of Experts architecture, in particular, offers a template for applying neutrosophic MCDM to other complex consumer decisions such as housing, education, and healthcare choices.

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Appendix

A.1 Aggregated Neutrosophic Pairwise Comparison Matrix

Table A1 presents the complete aggregated neutrosophic pairwise comparison matrix used for criterion weight derivation. Each cell contains the SVN $\langle T, I, F \rangle$ resulting from the SVNWA aggregation of four expert judgments.

Table A1. Aggregated neutrosophic pairwise comparison matrix

	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆
C ₁	$\langle .50, .30, .30 \rangle$	$\langle .60, .25, .20 \rangle$	$\langle .65, .20, .18 \rangle$	$\langle .70, .18, .15 \rangle$	$\langle .72, .15, .15 \rangle$	$\langle .80, .12, .10 \rangle$
C ₂	$\langle .40, .25, .35 \rangle$	$\langle .50, .30, .30 \rangle$	$\langle .58, .25, .22 \rangle$	$\langle .65, .20, .18 \rangle$	$\langle .70, .18, .15 \rangle$	$\langle .78, .14, .12 \rangle$
C ₃	$\langle .35, .20, .45 \rangle$	$\langle .42, .25, .38 \rangle$	$\langle .50, .30, .30 \rangle$	$\langle .58, .25, .22 \rangle$	$\langle .62, .22, .20 \rangle$	$\langle .72, .16, .14 \rangle$
C ₄	$\langle .30, .18, .52 \rangle$	$\langle .35, .20, .45 \rangle$	$\langle .42, .25, .38 \rangle$	$\langle .50, .30, .30 \rangle$	$\langle .55, .28, .25 \rangle$	$\langle .68, .18, .16 \rangle$
C ₅	$\langle .28, .15, .55 \rangle$	$\langle .30, .18, .52 \rangle$	$\langle .38, .22, .42 \rangle$	$\langle .45, .28, .35 \rangle$	$\langle .50, .30, .30 \rangle$	$\langle .62, .22, .20 \rangle$
C ₆	$\langle .20, .12, .68 \rangle$	$\langle .22, .14, .65 \rangle$	$\langle .28, .16, .58 \rangle$	$\langle .32, .18, .52 \rangle$	$\langle .38, .22, .45 \rangle$	$\langle .50, .30, .30 \rangle$

A.2 Chain of Experts Processing Log

Stage 1 (Domain Expert): Validated Guayaquil automotive market context. Confirmed availability of all five alternatives through authorized dealerships. Identified key market factors: import tariffs (35-45% on finished vehicles), fuel price volatility (Super gasoline averaging \$2.40-2.80/gallon), and limited public transportation alternatives driving private vehicle demand.

Stage 2 (MCDM Expert): Established decision hierarchy with six criteria. Rejected two proposed criteria: "brand reputation" (subjective and difficult to operationalize with neutrosophic scales) and "color options" (not a genuine performance criterion). Confirmed MECE properties of final criterion set.

Stage 3 (Neutrosophic Logic Expert): Defined nine-level linguistic scales for both pairwise comparisons and performance evaluation. Specified indeterminacy (I) interpretation: $I > 0.25$ indicates insufficient data for reliable assessment; $I > 0.35$ requires data collection before final decision.

Stage 4 (Consistency Expert): Detected 7 conflicts in raw expert inputs. Conflicts resolved: (a) C₁-C₃ comparison—Financial Analyst rated "Strongly More Important" while Environmental Specialist rated "Equally Important"; resolved to "Moderately More Important" with elevated $I=0.25$; (b) A₁ safety rating—Engineering Expert rated "Medium Poor" while End-User rated "Good"; resolved to "Medium" with $I=0.30$.

Stage 5 (Aggregation Expert): Computed all matrices and rankings using Equations 1-10. Verified computational accuracy through back-calculation of ideal solutions. Confirmed that CC coefficient rankings are consistent with score function rankings for all alternatives.

Stage 6 (Academic Writer): Structured final manuscript according to NCML requirements. Ensured consistent notation throughout. Verified all citations against original sources. Confirmed mathematical expression formatting and table/figure numbering.

A.3 Neutrosophic AHP-TOPSIS Algorithm

Algorithm 1: Neutrosophic AHP-TOPSIS with Chain of Experts

Input: Set of alternatives $A = \{A_1, A_2, \dots, A_m\}$; Set of criteria $C = \{C_1, C_2, \dots, C_n\}$; K expert profiles

Output: Ranked alternatives with closeness coefficients

Step 1: [Domain Expert] Validate alternatives and criteria for decision context

Step 2: [MCDM Expert] Structure decision hierarchy and verify MECE properties

Step 3: [Neutrosophic Expert] Define linguistic scales and T,I,F interpretation rules

Step 4: For each expert $k = 1$ to K :

4a. Elicit pairwise comparisons $\tilde{A}^{(k)}$ using linguistic scale

4b. Elicit performance evaluations $\tilde{D}^{(k)}$ using evaluation scale

Step 5: [Consistency Expert] Aggregate expert matrices using SVNWA (Eq. 4)

Step 6: [Consistency Expert] Detect and resolve conflicts where $\sigma(S) > 0.15$

Step 7: [Aggregation Expert] Compute criterion weights using Eq. 5

Step 8: [Aggregation Expert] Construct weighted normalized matrix using Eq. 6

Step 9: [Aggregation Expert] Identify NPIS A^+ and NNIS A^- using Eqs. 7-8

Step 10: [Aggregation Expert] Calculate separation measures using Eq. 9

Step 11: [Aggregation Expert] Compute closeness coefficients using Eq. 10

Step 12: Rank alternatives in descending order of CC values

Step 13: [Academic Writer] Document methodology and results per NCML standards

Return: Ranked alternatives with CC values and supporting documentation

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