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Optimizing Electric Vehicle Selection Using Neutrosophic SuperHyperSoft Set Theory

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Abstract: The rising demand for sustainable transportation has intensified the need for robust decision-making models in selecting optimal Electric Vehicles (EVs) for organizational fleets. Traditional evaluation methods often struggle to handle the uncertainty, vagueness, and complex interdependencies involved in real-world multi-criteria assessments. To address these limitations, this study proposes a novel Multi-Criteria Decision-Making (MCDM) framework based on Neutrosophic SuperHyperSoft Sets (NSHSS). The proposed model introduces a powerful way to incorporate linguistic expert assessments, enabling flexible representation of indeterminacy and subjectivity through Neutrosophic triplets. By defining five core evaluation criteria range and Battery Efficiency (RBE), Total Cost of Ownership (TCO), Safety and Reliability (SR), Charging Infrastructure Compatibility (CIC), and Technology and Connectivity (TC), each subdivided into four linguistic sub-criteria, the framework constructs an extensive NSHSS universe using power sets and Cartesian products, resulting in 1,048,576 elements and 1024 propositions. A novel aggregation mechanism using the Generalized Neutrosophic SuperHyperSoft Weighted Heronian Mean (GNSHSWHM) operator and a customized score function is developed to rank EV alternatives effectively. A numerical illustration involving four EVs is presented to demonstrate the effectiveness, scalability, and practicality of the approach. Additionally, an automated R-based computational model is implemented to support real-time decision analysis. The study contributes a scalable, uncertainty-resilient, and context-adaptive tool for strategic EV adoption, and can be extended to broader domains involving complex MCDM problems under uncertainty.

Keywords: SuperHypersoft Sets; Neutrosophic SuperHypersoft Sets, MCDM, Electric Vehicle Selection.

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1. Introduction

Decision-making problems often involve uncertainty, imprecision, and vagueness. Classical mathematical tools such as set theory, probability, and fuzzy logic address these challenges, but they have limitations in handling complex, multi-attribute decision-making scenarios. To overcome these limitations, several extensions of set theory have been proposed, among which soft set theory [12], hyper soft set theory [1,17], and super hyper soft set theory [16] play significant roles. Soft set theory, introduced by Molodtsov in 1999, provides a flexible and parameterized approach to deal with uncertainty. Unlike fuzzy and rough sets, which require additional structures such as membership functions or equivalence relations, soft set theory is purely based on a parameterized family of subsets. A soft set is a collection of approximate descriptions of an object, where each description depends on a set of parameters. It has been successfully applied in decision-making, data analysis, and artificial intelligence. Hyper soft set theory extends soft set theory by incorporating a more detailed structure through multi-attribute parameterization. Instead of associating a single set with a parameter, hyper soft sets group multiple attributes under a parameter, making them suitable for handling complex decision-making problems. This enhances their applicability in fields such as medical diagnosis, engineering optimization, and information retrieval.

1.1 Literature Review

The Heronian Mean [2], rooted in classical mathematics, is a special type of averaging operator that considers not only the individual values but also the interactions between them. Unlike traditional means such as the arithmetic or geometric mean, the HM operator blends the arithmetic, geometric, and harmonic means to provide a more nuanced aggregation, especially suitable when the criteria are interdependent. This unique property makes it particularly advantageous in MCDM environments where attribute interactions cannot be ignored. In recent years, the HM operator has been extensively integrated into various fuzzy and neutrosophic frameworks, such as Intuitionistic Fuzzy Sets, Pythagorean Fuzzy Sets, and Neutrosophic Sets, to handle uncertainty, imprecision, and inconsistency in expert judgments. By doing so, it enhances the decision-making process by enabling a more accurate representation of human reasoning under complex and uncertain environments. The generalized weighted Heronian mean operator [22], geometric Heronian operators are used to analzing the data. There are many Heronian operators used in the decision-making problems such as neutrosophic Dombi-based Heronian mean operator [21], Bipolar neutrosophic Dombi-based Heronian Mean Operator [22], T-spherical fuzzy Dombi-weighted power-partitioned Heronian mean operator [25], etc.

Author’s	Sets	Application area
Lu, M. [10]	Neutrosophic set	College English Teaching Quality Evaluation
Naz, S., et al. [13]	Single-Valued Neutrosophic Set	A Novel MAGDM Approach for Software Quality Assessment
Tang, M., & Sun, Y. [20]	Neutrosophic set	Evaluation of Track and Field Students in Sports Colleges.
Ye, J., & Yong, R. [23]	Neutrosophic set	landslide Control Scheme Selection
Zhao, L., & Du, S. [28]	double-valued neutrosophic sets	Teaching Quality Evaluation
Zhao, Y. [29]	Neutrosophic set	Evaluating Quality of University General Education

		Courses
Tan, Q. et al. [19]	Triangular Neutrosophic Cubic Linguistic Hesitant Fuzzy Set	Quality Assessment of Innovation and Entrepreneurship Talent Cultivation in Universities
Haque, T. S., et al. [8]	Trapezoidal Neutrosophic Set	E-learning App Selection
Durmuş, C. N., et al. [5]	Type-2 Neutrosophic Fuzzy Set	Evaluation of Banking Performance of the Balkan Countries
Fan, C., et al. [6]	Pythagorean Neutrosophic Set	Evaluation of Water Pollution Control Technology in Pulp and Paper Industry
Zhang, K., et al. [27]	Single-Valued Neutrosophic Set	International Shipping Operator Selection
Chen, Z., et al. [4]	Neutrosophic Set	Evaluation of Sports Tourism
Mohamed, M., & Elsayed, A. [11]	Bipolar Neutrosophic Set	Evaluating Financial Markets in Egypt
Jamil, M., et al. [9]	Bipolar Neutrosophic Set	Selection of Robot
Priyadharshini, S., & Mohanaselvi, S. [14]	Complex Single-Valued Neutrosophic Set	Green Supply Chain Management
Zhai, S., et al. [26]	Neutrosophic Set	Supplier Selection
Bui, Q. et al [3]	Spherical Neutrosophic Set	A Novel Distance-Based Evaluation Strategy
Gül, A. Y., et al. [7]	Interval Valued Neutrosophic Set	Drone Selection for Forest Surveillance and Fire Detection

1.2 Preliminaries

A Neutrosophic Set (NS) [16] is introduced by Florentin Smarandache to handle uncertainty, imprecision, vagueness, and inconsistencies in data. It extends classical, fuzzy, and intuitionistic fuzzy set theories by incorporating three independent components: (i)Truth Membership (T): The degree to which an element belongs to the set. (ii) Indeterminacy Membership (I): The degree of uncertainty or indeterminacy in membership. (iii) Falsity Membership (F): The degree to which an element does not belong to the set. Each of these values (T, I, F) is independently chosen from the real interval [0,1], and $0 \leq T + I + F \leq 3$. Super hyper soft set theory (SHSS) [6] is an advanced extension of hyper soft sets, offering a more refined structure for handling uncertainty. Let X be a universe of discourse, $P(X)$ its powerset and $z_1, z_2, \ldots z_n$ $(n \geq 1)$ distinct attributes with disjoint corresponding sets $Z_1, Z_2, \ldots Z_n$. The powerset of Z_k for k= $1, 2, \ldots n$ is denoted as $P(z_k)$. A SuperHyperSoft Set (SHSS) over X is defined as the pair $\left(\alpha,\ P(Z_2)\times \ldots \times P(Z_n)\right)$ where $\alpha : P(Z_1)\times \ldots \times P(Z_n) \rightarrow P(X)$. This definition provides a multi-layered approach to organizing data, enabling better modeling of multi-criteria decision-making problems. To

further enhance the expressiveness of SHSS, Neutrosophic Super Hyper Soft Set (NSHSS) [17, 18] theory introduces neutrosophic logic into the framework. Given the same universe X, its powerset P(X) and distinct attributes with disjoint corresponding sets, an NSHSS over X is defined as the pair $(\alpha,\ P(Z_1)\times \ldots \times P(Z_n))$ where
$\alpha : P(Z_1)\times \ldots \times P(Z_n)\rightarrow P(X)$. and
$\alpha = \{ y,\ \langle x, T_{\alpha(y)}(x), I_{\alpha(y)}(x), F_{\alpha(y)}(x)\rangle : x\in X, y\in P(Z_2)\times \ldots \times P(Z_n)) \}$.
Here $T_{\alpha(y)}(x), I_{\alpha(y)}(x), F_{\alpha(y)}(x): X \rightarrow [0,1]$ represent the membership, indeterminacy and non-membership degrees of $x\in X$ for each y, satisfying: $0 \leq T_{\alpha(y)}(x) + I_{\alpha(y)}(x) + F_{\alpha(y)}(x) \leq 3$.

Definition 1.2.1 [18]: Let X be a universe of discourse, $P(X)$ its powerset and $z_1, z_2, \ldots z_n$ $(n \geq 1)$ distinct attributes with disjoint corresponding sets $Z_1, Z_2, \ldots Z_n$. The powerset of Z_k for k= $1, 2, \ldots n$ is denoted as $P(z_k)$. Let $\gamma,\ \delta$ be two NSHSS over X is defined as the pair
$(\gamma, \mathcal{P}(z_1)\times \ldots \times \mathcal{P}(z_n))$ and $(\delta, \mathcal{P}(z_1)\times \ldots \times \mathcal{P}(z_n))$ where $\gamma, \delta : \mathcal{P}(z_1)\times \ldots \times \mathcal{P}(z_n) \rightarrow \mathcal{P}(X)$ and
$\gamma = \{ w, < u, \mathcal{T}_{\gamma(w)}(u), \mathcal{I}_{\gamma(w)}(u), \mathcal{F}_{\gamma(w)}(u) > : u\in X, w\in \mathcal{P}(z_1)\times \ldots \times \mathcal{P}(z)\}$
$\delta = \{ w, < v, \mathcal{T}_{\delta(w)}(v), \mathcal{I}_{\delta(w)}(v), \mathcal{F}_{\delta(w)}(v) > : v\in X,\ w\in \mathcal{P}(z_1)\times \ldots \times \mathcal{P}(z_n)\}$. Then the basic operators are defined as

1. $\gamma \oplus \delta = <\mathcal{T}_{\gamma(w)}(u) + \mathcal{T}_{\delta(w)}(v) - \mathcal{T}_{\gamma(w)}(u) . \mathcal{T}_{\delta(w)}(v), \mathcal{I}_{\gamma(w)}(u) . \mathcal{I}_{\delta(w)}(v), \mathcal{F}_{\gamma(w)}(u) . \mathcal{F}_{\delta(w)}(v)>$.
2. $\gamma \otimes \delta = < \mathcal{T}_{\gamma(w)}(u). \mathcal{T}_{\delta(w)}(v), \mathcal{I}_{\gamma(w)}(u) + \mathcal{I}_{\delta(w)}(v) - \mathcal{I}_{\gamma(w)}(u) . \mathcal{I}_{\delta(w)}(v), \mathcal{F}_{\gamma(w)}(u) + \mathcal{F}_{\delta(w)}(v) - \mathcal{F}_{\gamma(w)}(u) . \mathcal{F}_{\delta(w)}(v)>$.

Definition 1.2.2 : Let $\mathrm{N}_1, \mathrm{N}_2 \ldots, \mathrm{N}_\alpha$ be the collection of NSHSS. Then the Generalized Neutrosophic SuperHyperSoft Weighted Heronian Mean operator $\mathrm{GNSHSWHM}_{\mathrm{w}}^{\mathrm{A,B}}(\mathrm{N}_1, \mathrm{N}_2 \ldots, \mathrm{N}_\alpha)$ is

$$\mathbf{GNSHSWHM}_{\mathbf{w}}^{\mathbf{A,B}}(\mathbf{N}_1, \mathbf{N}_2 \ldots, \mathbf{N}_\alpha) = \begin{pmatrix} \left(\mathbf{1} - \prod_{\mathbf{C=1,D=1}}^{\alpha}\left(\mathbf{1} - \left(\mathbf{T}_{\mathbf{N_C}}\right)^{\mathbf{Aw_C}}\left(\mathbf{T}_{\mathbf{N_D}}\right)^{\mathbf{Bw}_D}\right)^{\frac{\mathbf{2}}{\alpha(\alpha+\mathbf{1})}}\right)^{\frac{\mathbf{1}}{\mathbf{A+B}}}, \\ \mathbf{1} - \left(\mathbf{1} - \prod_{\mathbf{C=1,D=1}}^{\alpha}\left(\mathbf{1} - \left(\mathbf{1} - \mathbf{F}_{\mathbf{N_C}}\right)^{\mathbf{Aw_C}}\left(\mathbf{1} - \mathbf{F}_{\mathbf{N_D}}\right)^{\mathbf{Bw}_D}\right)^{\frac{\mathbf{2}}{\alpha(\alpha+\mathbf{1})}}\right)^{\frac{\mathbf{1}}{\mathbf{A+B}}}, \\ \mathbf{1} - \left(\mathbf{1} - \prod_{\mathbf{C=1,D=1}}^{\alpha}\left(\mathbf{1} - \left(\mathbf{1} - \mathbf{I}_{\mathbf{N_C}}\right)^{\mathbf{Aw_C}}\left(\mathbf{1} - \mathbf{I}_{\mathbf{N_D}}\right)^{\mathbf{Bw}_D}\right)^{\frac{\mathbf{2}}{\alpha(\alpha+\mathbf{1})}}\right)^{\frac{\mathbf{1}}{\mathbf{A+B}}} \end{pmatrix}$$

Where $\sum_{1=1}^{n} w_i = 1$.

This study aims to enhance Multi-Criteria Decision-Making (MCDM) for electric vehicle (EV) selection using the Neutrosophic SuperHyperSoft Set (NSHSS) framework. Unlike traditional MCDM methods, which rigidly rank alternatives, NSHSS generates 1024 possible propositions, allowing decision-makers to select only the most relevant ones based on specific needs. By incorporating neutrosophic components (Truth, Indeterminacy, and Falsity), NSHSS effectively manages uncertainty and imprecision in decision-making. This structured approach improves flexibility, accuracy, and adaptability, ensuring an optimal EV selection process for corporate and governmental applications.

2. Selection of Electrical Vehicle Using NSHSS in MCDM

As part of its sustainability initiative, a corporation is planning to transition its vehicle fleet to electric vehicles (EVs). With numerous EV models available, the company must carefully select the most suitable vehicles based on various criteria such as performance, cost, environmental impact, and technological features. The selection process must consider the range and battery efficiency, ensuring that the vehicles can handle daily operational requirements without frequent recharging. Charging infrastructure compatibility is also critical, as the company must evaluate whether the vehicles align with existing or planned charging networks. Additionally, total cost of ownership, including purchase price, maintenance, and long-term operational expenses, plays a significant role in decision-making.

Further considerations include safety and reliability, government incentives and tax benefits, and technological features such as autonomous driving capabilities and smart connectivity. Given these complex and interdependent factors, the corporation will use a Multi-Criteria Decision-Making (MCDM) approach to systematically evaluate the available EV models. By applying MCDM techniques, the company ensures that its fleet transition aligns with sustainability goals, operational needs, and financial constraints while maximizing the benefits of EV adoption.

2.1 Algorithm for Multi Criteria Decision-Making Using NSHSS

Step 1: Initialize the Process : Identify the key components required for decision-making:

- Decision-makers (K): A set of experts $\{K_1, K_2, ..., K_n\}$.
- Criteria (C): The attributes influencing the decision $\{C_1, C_2, ..., C_n\}$.
- Alternatives (A): The available choices $\{A_1, A_2, ..., A_n\}$. Gather input data from decision-makers regarding the criteria and alternatives.

Step 2: Formulate Propositions Using NSHSS : Utilize attributes and sub-attributes to generate power sets of criteria and construct an NSHSS (Neutrosophic SuperHyperSoft Set) architecture.

Step 3: Linguistic Evaluation of Each Criterion : Convert decision-makers' linguistic evaluations into neutrosophic values for each criterion $C = \{C_1, C_2, ..., C_n\}$.

Step 4: Aggregate NSHSS Using $\mathrm{GNSHSWHM}_{w}^{A,B}$. Use the generalized neutrosophic superhypersoft weighted Heronian mean operator to combine evaluations across all criteria for each alternative:

$$\mathbf{GNSHSWHM}_{w}^{A,B}(\mathbf{N_1}, \mathbf{N_2} \dots, \mathbf{N_\alpha}) = \begin{pmatrix} \left(1 - \prod_{C=1,D=1}^{\alpha} \left(1 - \left(T_{N_C}\right)^{Aw_C} \left(T_{N_D}\right)^{Bw_D}\right)^{\frac{2}{\alpha(\alpha+1)}}\right)^{\frac{1}{A+B}}, \\ 1 - \left(1 - \prod_{C=1,D=1}^{\alpha} \left(1 - \left(1 - F_{N_C}\right)^{Aw_C} \left(1 - F_{N_D}\right)^{Bw_D}\right)^{\frac{2}{\alpha(\alpha+1)}}\right)^{\frac{1}{A+B}}, \\ 1 - \left(1 - \prod_{C=1,D=1}^{\alpha} \left(1 - \left(1 - I_{N_C}\right)^{Aw_C} \left(1 - I_{N_D}\right)^{Bw_D}\right)^{\frac{2}{\alpha(\alpha+1)}}\right)^{\frac{1}{A+B}} \end{pmatrix}$$

Step 5: Evaluate Alternatives Using a Score Function.

Compute the score for each alternative using: $S = \frac{2+T_a-I_a-F_a}{3}$

Step 6: Rank the Alternatives

Rank the alternatives A = {A_1, A_2, ..., A_n} based on their computed scores.

Step 7: Select the Best Alternative(s)

Choose the best alternative(s) based on the highest ranking obtained from the score function.

Step 8: End the Process

We will use the following R Programming code to calculate the generalized neutrosophic superhypersoft weighted Heronian mean operator.

```
compute_GNSHSWHM <-function(A,B,alpha,T,F,I,w){
term1<-(1-prod(1-(T^(A*w)*T^(B*w)))^(2/(alpha*(alpha+1))))^(1/(A+B))

term2<-1-(1-prod(1-((1-F)^(A*w)*(1-F)^(B*w)))^(2/(alpha*(alpha+1))))^(1/(A+B))

term3<-1-(1-prod(1-((1-I)^(A*w)*(1-I)^(B*w)))^(2/(alpha*(alpha+1))))^(1/(A+B))
return(c(term1,term2,term3))
}

main<-function(){
A<- as.numeric(readline("Enter value for A: "))
B <- as.numeric(readline("Enter value for B: "))
alpha <- as.integer(readline("Enter value for alpha: "))
cat("Enter values for T (comma-separated): ")
T <- as.numeric(unlist(strsplit(readline(), ",")))
cat("Enter values for F (comma-separated): ")
F <- as.numeric(unlist(strsplit(readline(), ",")))
cat("Enter values for I (comma-separated): ")
I <- as.numeric(unlist(strsplit(readline(), ",")))
cat("Enter weights w (comma-separated): ")
```

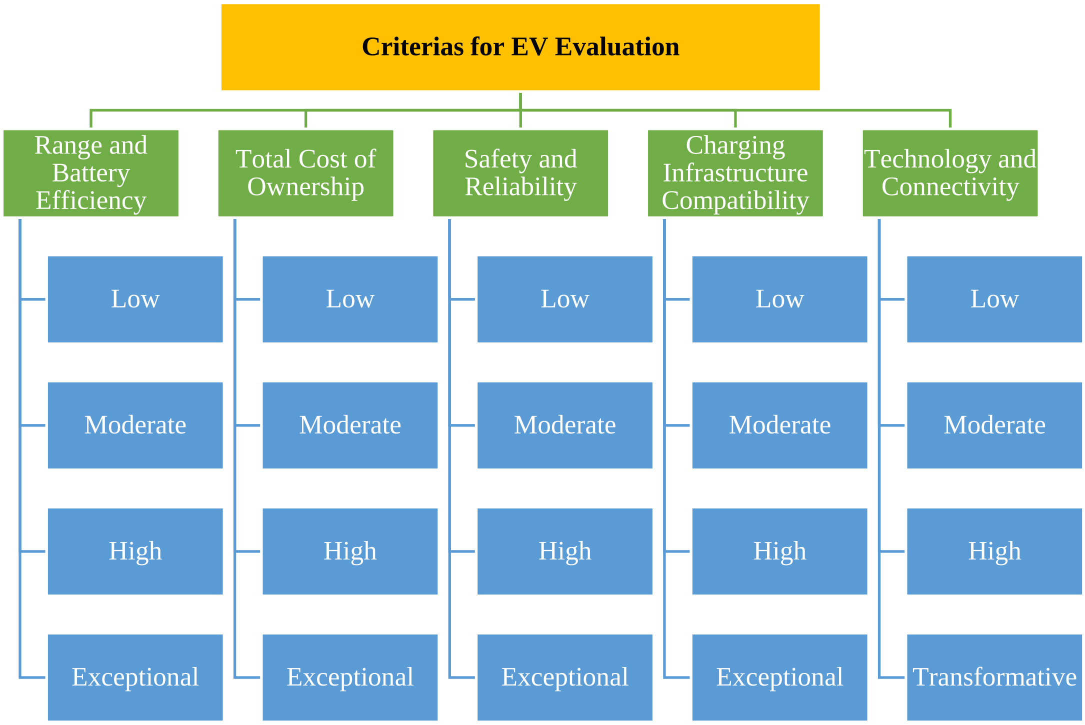
```
w <- as.numeric(unlist(strsplit(readline(), ",")))
result <- compute_GNSHSWHM(A, B, alpha, T, F, I, w)
cat("Computed GNSHSWHM values:\n")
cat("Term 1:", result[1], "\n")
cat("Term 2:", result[2], "\n")
cat("Term 3:", result[3], "\n")
}
main()
```

2.2 Numerical Example for Multi Criteria Decision-Making Using NSHSS

Step 1: Initialize the Process

Selection Criteria for EV Evaluation

1. Range and Battery Efficiency (RBE)
   - Low (RBE-L): <200 km range, slow charging speed
   - Moderate (RBE-M): 200-300 km range, moderate charging time
   - High (RBE-H): 300-400 km range, fast charging capability
   - Exceptional (RBE-E): >400 km range, ultra-fast charging, battery longevity
2. Total Cost of Ownership (TCO)
   - Low (TCO-L): High upfront cost, expensive maintenance, limited warranty
   - Moderate (TCO-M): Moderate initial cost, average maintenance expenses
   - High (TCO-H): Reasonable cost, extended warranty, cost-efficient operation
   - Exceptional (TCO-E): Low operating costs, long battery warranty, high resale value
3. Safety and Reliability (SR)
   - Low (SR-L): Basic safety features, minimal crash test ratings
   - Moderate (SR-M): Standard safety features, meets industry safety benchmarks
   - High (SR-H): Advanced driver assistance, high crash-test ratings
   - Exceptional (SR-E): Industry-leading safety features, autonomous driving capabilities
4. Charging Infrastructure Compatibility (CIC)
   - Low (CIC-L): Requires specialized charging stations, limited availability
   - Moderate (CIC-M): Compatible with some standard charging stations
   - High (CIC-H): Works with widely available fast-charging networks
   - Exceptional (CIC-E): Supports multiple charging standards, ultra-fast charging
5. Technology and Connectivity (TC)
   - Low (TC-L): Basic infotainment, minimal smart features
   - Moderate (TC-M): Some smart features, basic smartphone integration
   - High (TC-H): Advanced connectivity, self-parking, AI-assisted driving
   - Transformative (TC-T): Full smart integration, autonomous driving potential.



Step 2: Formulate Propositions Using NSHSS

2.3 SuperHyper Soft Sets

The power set of RBE is denoted by Δ(RBE) and Δ(RBE) = {∅,{RBE-L}, {RBE-M}, {RBE-H}, {RBE-E}, {RBE-L, RBE-M}, {RBE-L, RBE-H}, {RBE-L, RBE-E}, {RBE-M, RBE-H}, {RBE-M, RBE-E}, {RBE-H, RBE-E}, {RBE-L, RBE-M, RBE-H}, {RBE-L, RBE-M, RBE-E}, {RBE-L, RBE-H, RBE-E}, {RBE-M, RBE-H, RBE-E}, {RBE-L, RBE-M, RBE-H, RBE-E}}

The power set of TCO is denoted by Δ(TCO) and Δ(TCO) = {∅, {TCO-L}, {TCO-M}, {TCO-H}, {TCO-E}, {TCO-L, TCO-M}, {TCO-L, TCO-H}, {TCO-L, TCO-E}, {TCO-M, TCO-H}, {TCO-M, TCO-E}, {TCO-H, TCO-E}, {TCO-L, TCO-M, TCO-H}, {TCO-L, TCO-M, TCO-E}, {TCO-L, TCO-H, TCO-E}, {TCO-M, TCO-H, TCO-E}, {TCO-L, TCO-M, TCO-H, TCO-E}}

The power set of SR is denoted by Δ(SR) and Δ(SR) = {∅, {SR-L}, {SR-M}, {SR-H}, {SR-E}, {SR-L, SR-M}, {SR-L, SR-H}, {SR-L, SR-E}, {SR-M, SR-H}, {SR-M, SR-E}, {SR-H, SR-E}, {SR-L, SR-M, SR-H}, {SR-L, SR-M, SR-E}, {SR-L, SR-H, SR-E}, {SR-M, SR-H, SR-E}, {SR-L, SR-M, SR-H, SR-E}}

The power set of CIC is denoted by Δ(CIC) and Δ(CIC) = {∅, {CIC-L}, {CIC-M}, {CIC-H}, {CIC-E}, {CIC-L, CIC-M}, {CIC-L, CIC-H}, {CIC-L, CIC-E}, {CIC-M, CIC-H}, {CIC-M, CIC-E}, {CIC-H, CIC-E}, {CIC-L, CIC-M, CIC-H}, {CIC-L, CIC-M, CIC-E}, {CIC-L, CIC-H, CIC-E}, {CIC-M, CIC-H, CIC-E}, {CIC-L, CIC-M, CIC-H, CIC-E}}

The power set of TC is denoted by Δ(TC) and Δ(TC) = {∅, {TC-L}, {TC-M}, {TC-H}, {TC-T}, {TC-L, TC-M}, {TC-L, TC-H}, {TC-L, TC-T}, {TC-M, TC-H}, {TC-M, TC-T}, {TC-H, TC-T}, {TC-L, TC-M, TC-H}, {TC-L, TC-M, TC-T}, {TC-L, TC-H, TC-T}, {TC-M, TC-H, TC-T}, {TC-L, TC-M, TC-H, TC-T}}

The power set of U is denoted by Δ(U) and Δ(U) = {∅, {EV1}, {EV2}, {EV3}, {EV4}, {EV1, EV2}, {EV1, EV3}, {EV1, EV4}, {EV2, EV3}, {EV2, EV4}, {EV3, EV4}, {EV1, EV2, EV3}, {EV1, EV2, EV4}, {EV1, EV3, EV4}, {EV2, EV3, EV4}, {EV1, EV2, EV3, EV4}}

Let *F*: Δ(RBE) × Δ(TCO) × Δ(SR) × Δ(CIC) × Δ(TC) → Δ (U), where × denotes the Cartesian product for this equation. As a result, this is known as Neutrosophic SuperHyperSoft sets over $\mathfrak{R}$. The Cartesian product of Δ(RBE), Δ(TCO), Δ(SR), Δ(CIC), and Δ(TC) has 1,048,576elements.

Δ(RBE) × Δ(TCO) × Δ(SR) × Δ(CIC) × Δ(TC) = {(∅,∅,∅,∅,∅), (∅, ∅, ∅, ∅, {TC - L}), (∅, ∅, ∅, ∅, {TC - M}), (∅, ∅, ∅, ∅, {TC-H}), (∅, ∅, ∅, ∅, {TC-T}), (∅, ∅, ∅, ∅, {TC-L, TC-M}), (∅, ∅, ∅, ∅, {TC-L, TC-H}), (∅, ∅, ∅, ∅, {TC-L, TC-T}), (∅, ∅, ∅, ∅, {TC-M, TC-H}), (∅, ∅, ∅, ∅, {TC-M, TC-T}), (∅, ∅, ∅, ∅, {TC-H, TC-T}), (∅, ∅, ∅, ∅, {TC-L, TC-M, TC-H}), (∅, ∅, ∅, ∅, {TC-L, TC-M, TC-T}), (∅, ∅, ∅, ∅, {TC-L, TC-H, TC-T}), (∅, ∅, ∅, ∅, {TC-M, TC-H, TC-T}), (∅, ∅, ∅, ∅, {TC-L, TC-M, TC-H, TC-T}), (∅, ∅, ∅, {CIC-L}, ∅), (∅, ∅, ∅, {CIC-M}, ∅), (∅, ∅, ∅, {CIC-H}, ∅), (∅, ∅, ∅, {CIC-E}, ∅), (∅, ∅, ∅, {CIC-L, CIC-M}, ∅), (∅, ∅, ∅, {CIC-L, CIC-H}, ∅), (∅, ∅, ∅, {CIC-L, CIC-E}, ∅), (∅, ∅, ∅, {CIC-M, CIC-H}, ∅), (∅, ∅, ∅, {CIC-M, CIC-E}, ∅), (∅, ∅, ∅, {CIC-H, CIC-E}, ∅), (∅, ∅, ∅, {CIC-L, CIC-M, CIC-H}, ∅), (∅, ∅, ∅, {CIC-L, CIC-M, CIC-E}, ∅), (∅, ∅, ∅, {CIC-L, CIC-H, CIC-E}, ∅), (∅, ∅, ∅, {CIC-M, CIC-H, CIC-E}, ∅), (∅, ∅, ∅, {CIC-L, CIC-M, CIC-H, CIC-E}, ∅), (∅, ∅, {SR-L}, ∅, ∅), (∅, ∅, {SR-M}, ∅, ∅), (∅, ∅, {SR-H}, ∅, ∅), (∅, ∅, {SR-E}, ∅, ∅), (∅, ∅, {SR-L, SR-M}, ∅, ∅), (∅, ∅, {SR-L, SR-H}, ∅, ∅), (∅, ∅, {SR-L, SR-E}, ∅, ∅), (∅, ∅, {SR-M, SR-H}, ∅, ∅), (∅, ∅, {SR-M, SR-E}, ∅, ∅), (∅, ∅, {SR-H, SR-E}, ∅, ∅), (∅, ∅, {SR-L, SR-M, SR-H}, ∅, ∅), (∅, ∅, {SR-L, SR-M, SR-E}, ∅, ∅), (∅, ∅, {SR-L, SR-H, SR-E}, ∅, ∅), (∅, ∅, {SR-M, SR-H, SR-E}, ∅, ∅), (∅, ∅, {SR-L, SR-M, SR-H, SR-E}, ∅, ∅), (∅, {TCO-L}, ∅, ∅, ∅), (∅, {TCO-M}, ∅, ∅, ∅), (∅, {TCO-H}, ∅, ∅, ∅), (∅, {TCO-E}, ∅, ∅, ∅), (∅, {TCO-L, TCO-M}, ∅, ∅, ∅), (∅, {TCO-L, TCO-H}, ∅, ∅, ∅), (∅, {TCO-L, TCO-E}, ∅, ∅, ∅), (∅, {TCO-M, TCO-H}, ∅, ∅, ∅), (∅, {TCO-M, TCO-E}, ∅, ∅, ∅), (∅, {TCO-H, TCO-E}, ∅, ∅, ∅), etc.…}

The total number of possible combinations (propositions) is: 4 × 4 × 4 × 4 × 4 = 1024.

The following R Programming code can be used to generate all the propositions.

```
generate_propositions <- function(criteria) {
  options <- expand.grid(criteria, stringsAsFactors = FALSE)
  propositions <- apply(options, 1, function(row) {
    paste("(", paste(row, collapse = ", "), ")", sep = "")
  })
  return(propositions)
}

main <- function() {
```

```
  cat("Enter the number of criteria: ")
  num_criteria <- as.integer(readLines(n = 1))
  criteria <- list()

  for (i in 1:num_criteria) {
    cat(paste("Enter name for criteria", i, ": "))
    criteria_name <- readLines(n = 1)
    cat(paste("Enter options for", criteria_name, "(comma-separated): "))
    options <- unlist(strsplit(readLines(n = 1), ","))
    criteria[[criteria_name]] <- options
  }

  propositions <- generate_propositions(criteria)
  total_combinations <- length(propositions)

  cat("The total number of possible combinations (propositions) is:",
total_combinations, "\n")
  cat("The following are a few examples:\n")

  for (i in 1:min(10, total_combinations)) {
    cat(i, ". ", propositions[i], "\n", sep = "")
  }
}

main()
```

The following are few example:

1. (RBE-L, TCO-L, SR-L, CIC-L, TC-L) → An EV with low range and battery efficiency, high ownership cost, low safety, minimal charging compatibility, and basic technology.
2. (RBE-L, TCO-L, SR-L, CIC-L, TC-M) → An EV with low range and battery efficiency, high ownership cost, low safety, minimal charging compatibility, and some smart features.
3. (RBE-L, TCO-L, SR-L, CIC-L, TC-H) → An EV with low range and battery efficiency, high ownership cost, low safety, minimal charging compatibility, and advanced connectivity.
4. (RBE-L, TCO-L, SR-L, CIC-L, TC-T) → An EV with low range and battery efficiency, high ownership cost, low safety, minimal charging compatibility, and fully integrated autonomous technology.
5. (RBE-L, TCO-L, SR-L, CIC-M, TC-L) → An EV with low range and battery efficiency, high ownership cost, low safety, compatible with some charging stations, and basic technology.
6. (RBE-L, TCO-L, SR-L, CIC-M, TC-M) → An EV with low range and battery efficiency, high ownership cost, low safety, compatible with some charging stations, and some smart features.
7. (RBE-L, TCO-L, SR-L, CIC-M, TC-H) → An EV with low range and battery efficiency, high ownership cost, low safety, compatible with some charging stations, and advanced connectivity.
8. (RBE-L, TCO-L, SR-L, CIC-M, TC-T) → An EV with low range and battery efficiency, high

ownership cost, low safety, compatible with some charging stations, and fully integrated autonomous technology.

9. (RBE-L, TCO-L, SR-L, CIC-H, TC-L) → An EV with low range and battery efficiency, high ownership cost, low safety, widely available fast charging, and basic technology.
10. (RBE-L, TCO-L, SR-L, CIC-H, TC-M) → An EV with low range and battery efficiency, high ownership cost, low safety, widely available fast charging, and some smart features.

…………………………………………………………………………………………

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………………………………………………………………………………………….

1015. (RBE-E, TCO-E, SR-E, CIC-H, TC-H) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, widely available fast charging, and advanced connectivity.
1016. (RBE-E, TCO-E, SR-E, CIC-H, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, widely available fast charging, and fully integrated autonomous technology.
1017. (RBE-E, TCO-E, SR-E, CIC-E, TC-L) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and basic technology.
1018. (RBE-E, TCO-E, SR-E, CIC-E, TC-M) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and some smart features.
1019. (RBE-E, TCO-E, SR-E, CIC-E, TC-H) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and advanced connectivity.
1020. (RBE-E, TCO-E, SR-E, CIC-E, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and fully integrated autonomous technology.
1021. (RBE-E, TCO-E, SR-E, CIC-E, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and fully integrated autonomous technology.
1022. (RBE-E, TCO-E, SR-E, CIC-E, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and fully integrated autonomous technology.
1023. (RBE-E, TCO-E, SR-E, CIC-E, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and fully integrated autonomous technology.
1024. (RBE-E, TCO-E, SR-E, CIC-E, TC-T) → An EV with exceptional range, exceptional cost efficiency, top-tier safety, ultra-fast charging compatibility, and fully integrated autonomous technology.

Out of 1024 possible propositions, we have chosen two based on common requirements:

1. Most Affordable & Practical Choice (RBE-M, TCO-E, SR-M, CIC-M, TC-M)

   An EV with moderate range, exceptional cost efficiency, standard safety, moderate charging compatibility, and basic smart features—perfect for city driving with low maintenance costs and decent charging options.

2. Future-Proofed Yet Cost-Effective (RBE-M, TCO-E, SR-H, CIC-H, TC-H)

An EV with moderate range, exceptional cost efficiency, high safety, widely available charging, and advanced connectivity—great for buyers who want a safer, connected car without overspending.

Step 3: Linguistic Evaluation of Each Criterion

2.3 Neutrosophic SuperHyper Soft sets in MCDM

Neutrosophic SuperHyper Soft Sets (NSHSS) provide an advanced decision-making framework that integrates uncertainty, imprecision, and incomplete information. In this section, we define the selection symbols used in the evaluation of electric vehicles (EVs). Each symbol represents a specific linguistic term mapped to a corresponding triplet (T, I, F) in decimal format, where T represents truth membership, I represent indeterminacy membership, and F represents falsity membership.

EV Selection Symbol	Notation	(T, I, F) in Decimal
Extremely Low	α̋_{101}	(0.0, .949, .949)
Very Low	α̋_{102}	(0.199, 0.949, 0.849)
Low	α̋_{103}	(0.299, 0.799, 0.749)
Slightly Low	α̋_{104}	(0.399, 0.749, 0.699)
Below Moderate	α̋_{105}	(0.499, 0.649, 0.599)
Moderate	α̋_{106}	(0.699, 0.599, 0.499)
Above Moderate	α̋_{107}	(0.699, 0.449, 0.399)
Slightly High	α̋_{108}	(0.799, 0.299, 0.349)
High	α̋_{109}	(0.849, 0.249, 0.299)
Very High	α̋_{110}	(0.899, 0.199, 0.199)
Extremely High	α̋_{111}	(.999, 0.099, 0.099)

Table 1: EV Selection Symbols and Their Corresponding Notations

To evaluate EVs comprehensively, we consider multiple criteria and their corresponding sub-criteria. The table below assigns selection symbols to various EV options (EV1, EV2, EV3, and EV4) under different sub-criteria.

Criteria	Sub Criteria	EV1	EV2	EV3	EV4
RBE	RBE-L	α̋_{104}	α̋_{102}	α̋_{102}	α̋_{101}
	RBE-M	α̋_{105}	α̋_{106}	α̋_{107}	α̋_{106}
	RBE-H	α̋_{110}	α̋_{108}	α̋_{109}	α̋_{110}
	RBE- E	α̋_{111}	α̋_{109}	α̋_{110}	α̋_{108}
TCO	TCO-L	α̋_{102}	α̋_{103}	α̋_{104}	α̋_{102}
	TCO-M	α̋_{106}	α̋_{107}	α̋_{106}	α̋_{105}

	TCO-H	$\tilde{\alpha}_{108}$	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{110}$
	TCO-E	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{108}$	$\tilde{\alpha}_{111}$
SR	SR-L	$\tilde{\alpha}_{103}$	$\tilde{\alpha}_{101}$	$\tilde{\alpha}_{104}$	$\tilde{\alpha}_{103}$
	SR-M	$\tilde{\alpha}_{107}$	$\tilde{\alpha}_{106}$	$\tilde{\alpha}_{105}$	$\tilde{\alpha}_{106}$
	SR-H	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{111}$
	SR-E	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{108}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{111}$
CIC	CIC-L	$\tilde{\alpha}_{102}$	$\tilde{\alpha}_{101}$	$\tilde{\alpha}_{104}$	$\tilde{\alpha}_{102}$
	CIC-M	$\tilde{\alpha}_{105}$	$\tilde{\alpha}_{106}$	$\tilde{\alpha}_{107}$	$\tilde{\alpha}_{107}$
	CIC-H	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{111}$	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$
	CIC-E	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{108}$
TC	TC-L	$\tilde{\alpha}_{103}$	$\tilde{\alpha}_{101}$	$\tilde{\alpha}_{104}$	$\tilde{\alpha}_{101}$
	TC-M	$\tilde{\alpha}_{106}$	$\tilde{\alpha}_{107}$	$\tilde{\alpha}_{106}$	$\tilde{\alpha}_{105}$
	TC-H	$\tilde{\alpha}_{111}$	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{109}$
	TC-T	$\tilde{\alpha}_{109}$	$\tilde{\alpha}_{110}$	$\tilde{\alpha}_{108}$	$\tilde{\alpha}_{110}$

Table 2: Linguistic Evaluation of EV

The same criteria and EV selection process are now presented using precise numerical values corresponding to the selection symbols. This provides a numerical representation of the decision-making process for better analysis.

Criteria	Sub Criteria	EV1	EV2	EV3	EV4
RBE	RBE-L	(0.399, 0.749, 0.699)	(0.199, 0.949, 0.849)	(0.199, 0.949, 0.849)	(0.0, .949, .949)
	RBE-M	(0.499, 0.649, 0.599)	(0.699, 0.599, 0.499)	(0.699, 0.449, 0.399)	(0.699, 0.599, 0.499)
	RBE-H	(0.899, 0.199, 0.199)	(0.799, 0.299, 0.349)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)
	RBE- E	(.999, 0.099, 0.099)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.799, 0.299, 0.349)
TCO	TCO-L	(0.199, 0.949, 0.849)	(0.299, 0.799, 0.749)	(0.399, 0.749, 0.699)	(0.199, 0.949, 0.849)
	TCO-M	(0.699, 0.599, 0.499)	(0.699, 0.449, 0.399)	(0.699, 0.599, 0.499)	(0.499, 0.649, 0.599)
	TCO-H	(0.799, 0.299, 0.349)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.899, 0.199, 0.199)
	TCO-E	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.799, 0.299, 0.349)	(.999, 0.099, 0.099)
SR	SR-L	(0.299, 0.799, 0.749)	(0.0, .949, .949)	(0.399, 0.749, 0.699)	(0.299, 0.799, 0.749)

	SR-M	(0.699, 0.449, 0.399)	(0.699, 0.599, 0.499)	(0.499, 0.649, 0.599)	(0.699, 0.599, 0.499)
	SR-H	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.849, 0.249, 0.299)	(.999, 0.099, 0.099)
	SR-E	(0.899, 0.199, 0.199)	(0.799, 0.299, 0.349)	(0.899, 0.199, 0.199)	(.999, 0.099, 0.099)
CIC	CIC-L	(0.199, 0.949, 0.849)	(0.0, .949, .949)	(0.399, 0.749, 0.699)	(0.199, 0.949, 0.849)
	CIC-M	(0.499, 0.649, 0.599)	(0.699, 0.599, 0.499)	(0.699, 0.449, 0.399)	(0.699, 0.449, 0.399)
	CIC-H	(0.849, 0.249, 0.299)	(.999, 0.999, 0.099)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)
	CIC-E	(0.899, 0.199, 0.199)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.799, 0.299, 0.349)
TC	TC-L	(0.299, 0.799, 0.749)	(0.0, .949, .949)	(0.399, 0.749, 0.699)	(0.0, .949, .949)
	TC-M	(0.499, 0.649, 0.599)	(0.699, 0.449, 0.399)	(0.699, 0.599, 0.499)	(0.499, 0.649, 0.599)
	TC-H	(.999, 0.099, 0.099)	(0.849, 0.249, 0.299)	(0.899, 0.199, 0.199)	(0.849, 0.249, 0.299)
	TC-T	(0.849, 0.249, 0.299)	(.999, 0.099, 0.099)	(0.799, 0.299, 0.349)	(0.899, 0.199, 0.199)

Table 3: Numerical Neutrosophic Representation of EV Evaluation

Most Affordable & Practical Choice (RBE-M, TCO-E, SR-M, CIC-M, TC-M)

An EV with moderate range, exceptional cost efficiency, standard safety, moderate charging compatibility, and basic smart features perfect for city driving with low maintenance costs and decent charging options.

	RBE-M	**TCO-E**	**SR-M**	**CIC-M**	**TC-M**
EV1	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.699, 0.449, 0.399)	(0.499, 0.649, 0.599)	(0.499, 0.649, 0.599)
EV2	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.699, 0.449, 0.399)	(0.499, 0.649, 0.599)	(0.499, 0.649, 0.599)
EV3	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.699, 0.449, 0.399)	(0.499, 0.649, 0.599)	(0.499, 0.649, 0.599)
EV4	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.699, 0.449, 0.399)	(0.499, 0.649, 0.599)	(0.499, 0.649, 0.599)

Table 4: Most Affordable & Practical Choice

Step 4: Aggregate NSHSS Using $\mathrm{GNSHSWHM}_{w}^{A,B}$.

We calculate generalized neutrosophic superhypersoft weighted Heronian mean operator and the values are given in Table 5. Here we use equal weightage for all the criteria.

EV/ Method	$\mathbf{GNSHSWHM_{w}^{1,1}}$	$\mathbf{GNSHSWHM_{w}^{1,2}}$	$\mathbf{GNSHSWHM_{w}^{2,1}}$
EV1	(0.026, 0.052, 0.050)	(0.021, 0.042, 0.040)	(0.0387, 0.0763, 0.0737)
EV2	(0.007, 0.042, 0.032)	(0.006, 0.034, 0.026)	(0.0114, 0.0622, 0.0482)
EV3	(0.022, 0.044, 0.042)	(0.018, 0.036, 0.034)	(0.0340, 0.0658, 0.0634)
EV4	(0.007, 0.036, 0.028)	(0.006, 0.029, 0.023)	(0.0114, 0.0535, 0.043)

Table 5: GNSHSWHM Calculation Results

Step 5: Evaluate Alternatives Using a Score Function

Using Score function we calculate the crisp value for each EV and shown in Table 6.

Method/ EV	EV1	EV2	EV3	EV4
$\mathbf{GNSHSWHM_{w}^{1,1}}$	0.6412	0.6442	0.6452	0.6476
$\mathbf{GNSHSWHM_{w}^{1,2}}$	0.6462	0.6486	0.6494	0.6513
$\mathbf{GNSHSWHM_{w}^{2,1}}$	0.6296	0.6336	0.6349	0.6383

Table 6: Crisp Values of Each EV

Step 6: Rank the Alternatives

The ranking of EV's is given in Table

Method	Results	Best EV
$\mathbf{GNSHSWHM_{w}^{1,1}}$	EV4 > EV3 > EV2 > EV1	EV4
$\mathbf{GNSHSWHM_{w}^{1,2}}$	EV4 > EV3 > EV2 > EV1	EV4
$\mathbf{GNSHSWHM_{w}^{2,1}}$	EV4 > EV3 > EV2 > EV1	EV4

Table 7: Ranking of EVs

The final ranking of EVs based on these calculations confirms that EV4 is the best choice among the evaluated options.

Proposition 2: Future-Proofed Yet Cost-Effective (RBE-M, TCO-E, SR-H, CIC-H, TC-H)

An EV with moderate range, exceptional cost efficiency, high safety, widely available charging, and advanced connectivity great for buyers who want a safer, connected car without overspending.

	RBE-M	TCO-E	SR-H	CIC-H	TC-H
EV1	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(.999, 0.099, 0.099)
EV2	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(.999, 0.099, 0.099)
EV3	(0.499, 0.649,	(0.849, 0.249,	(0.849, 0.249,	(0.849, 0.249,	(.999, 0.099,

	0.599)	0.299)	0.299)	0.299)	0.099)
EV4	(0.499, 0.649, 0.599)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(0.849, 0.249, 0.299)	(.999, 0.099, 0.099)

Table 8: Future-Proofed Yet Cost-Effective

We calculate generalized neutrosophic superhypersoft weighted Heronian mean operator and the values are given in Table Here we use common weight for all the criteria.

	$\mathbf{GNSHSWHM_w^{1,1}}$	$\mathbf{GNSHSWHM_w^{1,2}}$	$\mathbf{GNSHSWHM_w^{2,1}}$
EV1	(0.006, 0.023, 0.026)	(0.005, 0.018, 0.021)	(0.0098, 0.0344, 0.0398)
EV2	(0.004, 0.017, 0.017)	(0.003, 0.014, 0.013)	(0.0059, 0.0267, 0.0255)
EV3	(0.010, 0.023, 0.026)	(0.008, 0.018, 0.021)	(0.0159, 0.0349, 0.0397)
EV4	(0.001, 0.015, 0.014)	(0.001, 0.012, 0.011)	(0.0021, 0.0228, 0.0218)

Table 9: GNSHSWHM Calculation Results

Calculation of $\mathrm{GNSHSWHM_w^{1,1}}$ EV1- True Value

$$=\left\{1-\left[\{1-(0.499^{0.2}\times 0.499^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.999^{0.2}\times 0.999^{0.2})\times 1-(0.499^{0.2}\times 0.849^{0.2})\times 1-(0.499^{0.2}\times 0.849^{0.2})\times 1-(0.499^{0.2}\times 0.849^{0.2})\times 1-(0.499^{0.2}\times 0.999^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.849^{0.2}\times 0.999^{0.2})\times 1-(0.849^{0.2}\times 0.849^{0.2})\times 1-(0.849^{0.2}\times 0.999^{0.2})\times 1-(0.849^{0.2}\times 0.999^{0.2})\}^{\frac{1}{10}}\right]^{\frac{1}{2}}\right\}$$

=0.006

Using Score function we calculate the crisp value for each EV and shown in Table 11.

Method/ EV	EV1	EV2	EV3	EV4
$\mathbf{GNSHSWHM_w^{1,1}}$	0.6523	0.6565	0.6538	0.6574
$\mathbf{GNSHSWHM_w^{1,2}}$	0.6551	0.6585	0.6562	0.6592
$\mathbf{GNSHSWHM_w^{2,1}}$	0.6450	0.6511	0.6470	0.6524

Table 10: Crisp Values of Each EV

Calculation of Score Function in $\mathrm{GNSHSWHM_w^{1,1}}$:

EV1= (2+0.006-0.023-0.026)/3 =0.6523

EV2= (2+0.004-0.017-0.017)/3 =0.6565

EV3= (2+0.010-0.023-0.026)/3 =0.6538

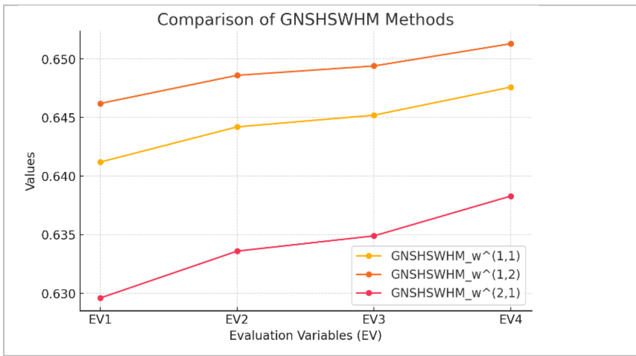
EV4= (2+0.001-0.015-0.014)/3 =0.6574

The ranking of EV's is given in Table

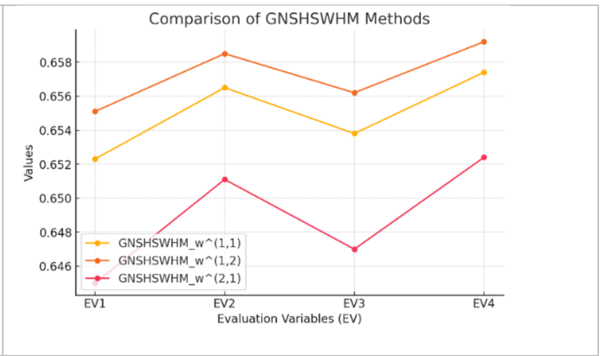
Method	Results	Best EV
$\mathbf{GNSHSWHM_w^{1,1}}$	EV4 > EV2 > EV3 > EV1	EV4
$\mathbf{GNSHSWHM_w^{1,2}}$	EV4 > EV2 > EV3 > EV1	EV4
$\mathbf{GNSHSWHM_w^{2,1}}$	EV4 > EV2 > EV3 > EV1	EV4

Table 11: Ranking of EVs

The final ranking of EVs based on these calculations confirms that EV4 is the best choice among the evaluated options.



Graphical Representation of Ranking of Proposition 1



Graphical Representation of Ranking of Proposition 2

2.4 Comparison with Related Methods

We took the different values for A and B in both the propositions, and we compared the methods proposed in this paper with other related methods proposed in the literature

Method	Results	Best EV
Tan, Q. et al. [19]	EV4 > EV2 > EV3 > EV1	EV4
Haque, T. S., et al. [8]	EV3 > EV4 > EV2 > EV1	EV3
Durmuş, C. N., et al. [5]	EV4 > EV3 > EV2 > EV1	EV4
Fan, C., et al. [6]	EV3 > EV2 > EV4 > EV1	EV3
Zhang, K., et al. [27]	EV4 > EV2 > EV3 > EV1	EV4
Proposition-2 $\mathrm{GNSHSWHM}_w^{1,1}$	EV4 > EV2 > EV3 > EV1	EV4
Proposition-2 $\mathrm{GNSHSWHM}_w^{1,2}$	EV4 > EV2 > EV3 > EV1	EV4
Proposition-2 $\mathrm{GNSHSWHM}_w^{2,1}$	EV4 > EV2 > EV3 > EV1	EV4
Proposition-1 $\mathrm{GNSHSWHM}_w^{1,1}$	EV4 > EV3 > EV2 > EV1	EV4
Proposition-1 $\mathrm{GNSHSWHM}_w^{1,2}$	EV4 > EV3 > EV2 > EV1	EV4
Proposition-1 $\mathrm{GNSHSWHM}_w^{2,1}$	EV4 > EV3 > EV2 > EV1	EV4

A ccomparison with related methods was conducted to assess the impact of varying expert weights and sub-criteria importance: Minor deviations in linguistic input values (T, I, F) showed limited influence on final rankings, confirming the stability of the aggregation and score functions. However, significant shifts in criteria weights (e.g., prioritizing TCO over RBE) led to noticeable changes in rankings, highlighting the model's responsiveness and transparency to stakeholder preferences. The model remains consistent in identifying the top-tier EVs under different weighting scenarios, validating its robustness.

2.5 Limitations

While the NSHSS framework offers robust handling of uncertainty and interdependencies, the following limitations are acknowledged: Computational intensity increases exponentially with additional criteria or sub-criteria, requiring efficient memory and processing strategies. Subjectivity in linguistic evaluations may influence final rankings if expert weights are not appropriately calibrated. The current model assumes static criteria and does not accommodate evolving real-time data or user feedback loops.

3. Conclusion

This study introduces a comprehensive decision-support framework based on Neutrosophic SuperHyperSoft Sets (NSHSS), effectively addressing the complexities of Electric Vehicle (EV) selection under uncertainty. By integrating linguistic expert assessments, neutrosophic representation, structured proposition modeling, and the GNSHSWHM operator, the proposed model facilitates nuanced evaluation across five key criteria and their sub-dimensions. The R-based implementation ensures computational feasibility and real-time applicability, empowering organizations to make transparent, sustainable, and data-driven fleet decisions. The model's flexibility and adaptability make it a strong foundation for future research in dynamic, multi-agent, and large-scale decision environments.

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