



An Explainable Artificial Intelligence-Based Intelligent Decision Framework for Sustainable Supplier Selection Under Uncertainty

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Abstract: Intelligent supplier selection is an important component of industrial supply chain management, where economic performance, environmental sustainability, social responsibility, and operational reliability must be considered under uncertain and often conflicting information. Although machine learning supports data-driven supplier evaluation, integrating predictive explanations with uncertainty-aware decision models remains a challenge. This study investigates an explainable artificial intelligence (XAI)-based framework for intelligent supplier selection by combining gradient boosting, Shapley value analysis, and multi-polar interval-valued neutrosophic hypersoft sets (m -Polar IVNHSS). A class of concave generator functions was developed to construct weighted distance and similarity measures using sine, exponential, hyperbolic-tangent, and hybrid functions. The proposed measures were shown to satisfy the metric axioms under positive weights, while a tangent-based measure was demonstrated to violate the triangle inequality. Shapley values derived from a gradient-boosting classifier were used to select relevant supplier sub-attributes, determine criterion weights, and support interpretable candidate screening. The framework was evaluated through three simulated industrial supplier selection cases involving electric-vehicle battery cells, organic-cotton fabric, and compostable packaging. Validation on 150 held-out suppliers per case yielded area under the receiver operating characteristic curve (AUC) values of 0.802, 0.630, and 0.837 for the hybrid similarity measure. Ablation experiments showed that data-driven sub-attribute selection contributed more to predictive discrimination than weight adjustment, while sensitivity analysis identified the hybrid generator as the most stable option among the proposed parameterized measures. These findings indicate that explainable machine learning and uncertainty-aware similarity measures can be integrated into a transparent industrial decision framework. The proposed approach provides a mathematically grounded basis for interpretable supplier ranking and supports the development of intelligent procurement decision systems, although validation using real industrial data remains necessary.

Keywords: Industrial intelligent decision-making; Explainable artificial intelligence; Sustainable supplier selection; Gradient boosting; Shapley values; Neutrosophic hypersoft sets; Uncertainty-aware decision support

1 Introduction

Supplier selection plays an important role in industrial supply chain management, as the reliability, quality and sustainability of external suppliers directly affect manufacturing performance and business continuity. Industrial enterprises must evaluate suppliers against several competing criteria, including purchasing costs, environmental performance, labour practices and operational reliability. These decisions become particularly difficult when information is incomplete, evaluation criteria are interdependent, and different departments hold conflicting assessments [1]. The increasing availability of industrial and supplier-related data has created opportunities to support procurement decisions through artificial intelligence (AI), machine learning and intelligent decision-support systems. Recent studies have highlighted the growing role of these technologies in supply chain management, while also identifying substantial challenges in translating analytical capabilities into reliable procurement decisions [2–4].

Intelligent supplier selection involves more than predicting whether a supplier will perform satisfactorily. Procurement managers must understand which supplier characteristics influence the results, how evaluation criteria are weighted and whether the resulting rankings remain dependable under uncertain conditions. Existing research on AI-supported procurement has demonstrated the potential of machine learning to analyse supplier information and support purchasing activities [5]. Hybrid approaches combining machine learning with multi-criteria decision-making have also been developed to retain interpretable decision procedures while using historical data to identify relevant supplier characteristics [6]. Nevertheless, industrial decision systems must accommodate both uncertainty in supplier assessments and the need for explanations that can be examined by procurement specialists and other stakeholders. Explainable artificial intelligence (XAI) has therefore become an important consideration in the development of data-driven supply chain decision systems [7].

Uncertainty modelling provides another essential component of intelligent industrial decision-making. Conventional numerical assessments may not adequately represent incomplete evidence, conflicting opinions or uncertainty concerning future supplier performance. Fuzzy sets were introduced to represent graded membership rather than strictly binary classifications [8], while intuitionistic fuzzy sets incorporated membership and non-membership degrees [9]. Neutrosophic sets subsequently introduced an additional indeterminacy component, allowing truth, indeterminacy and falsity to be represented independently [10]. Interval-valued neutrosophic sets further allow these assessments to be expressed as ranges rather than precise numerical values [11]. Developments in soft set theory [12], neutrosophic soft sets [13], interval-valued extensions [14] and hypersoft sets [15] have provided increasingly flexible representations of multi-attribute decision problems.

Saqlain and Xin [16] extended these concepts to multi-polar interval-valued neutrosophic hypersoft sets (m -Polar IVNHSS), which combine multiple poles, interval-valued evaluations and sub-attribute-based parameterisation. For industrial supplier assessment, this structure offers a way to represent the perspectives of different organisational units, planning horizons or information sources within a common mathematical framework. Such a representation is particularly relevant when procurement, sustainability and operations departments evaluate the same supplier using different information or when the available evidence varies in precision.

The practical use of m -Polar IVNHSS requires appropriate methods for comparing uncertain evaluations and ranking alternatives. Distance and similarity measures for related neutrosophic structures have been investigated in earlier research, and a more recent study introduced similarity measures for m -Polar IVNHSS sets together with a machine learning application [17]. Hamming- and Euclidean-type distances [18], vector-based similarity measures [19] and tangent-based formulations [20, 21] provide additional mathematical foundations for comparison. However, existing approaches generally focus on particular functional forms. A broader question concerns the conditions under which a transformation of endpoint differences yields a valid metric. This issue is important because a measure used in an industrial decision-support system should provide mathematically consistent comparisons, particularly when it is extended to clustering, consensus analysis or comparisons between supplier profiles. The triangle inequality is one of the essential properties in this respect.

A further challenge concerns the construction of the decision model itself. Hypersoft evaluation requires the selection of a sub-attribute from each broader criterion and the assignment of suitable criterion weights. In many multi-criteria decision procedures, these choices depend primarily on expert judgement. Although expert knowledge remains valuable, historical supplier performance data may reveal relationships that are difficult to identify through subjective assessments alone. Shapley-value analysis provides a principled method of attributing a model prediction to individual input features [22]. Its application to machine learning explanations [23], including interventional feature attribution [24], offers a basis for identifying influential supplier characteristics. Combined with gradient boosting [25], these explanations can support data-driven sub-attribute selection, criterion weighting and candidate screening while retaining an interpretable connection between historical performance patterns and the final decision.

This study develops an XAI-based intelligent decision framework for sustainable supplier selection under uncertainty. The framework integrates gradient-boosting prediction, Shapley-based feature attribution and m -Polar IVNHSS similarity measures. Its purpose is not simply to introduce another supplier ranking procedure, but to connect data-driven feature selection with mathematically defined uncertainty-aware comparisons. In this way, machine learning provides evidence for constructing the decision model, while the resulting similarity measures support the evaluation and ranking of candidate suppliers.

The main contributions of the study are as follows.

(1) Generalised distance and similarity measures. A class of concave generator functions is introduced for constructing weighted distance and similarity measures on m -Polar IVNHSS. Four nonlinear generators, based on sine, exponential, hyperbolic-tangent and hybrid functions, are examined. The construction provides a common mathematical basis for comparing uncertain evaluations rather than treating each functional form independently.

(2) Mathematical properties and theoretical comparison. The proposed distance measures are shown to satisfy the metric axioms when the relevant weights are strictly positive, while non-negative weights permit the corresponding pseudometric formulation. The theoretical analysis also examines the properties of associated similarity measures,

identifies a triangle-inequality violation in a tangent-based formulation and establishes relationships with simpler neutrosophic hypersoft structures.

(3) Explainable industrial decision framework. Gradient boosting and Shapley-value analysis are integrated with m -Polar IVNHSS to support intelligent supplier evaluation. Feature attributions are used to select relevant sub-attributes, determine criterion weights and screen candidate suppliers. The resulting procedure connects predictive information with interpretable multi-criteria decision-making under uncertainty.

(4) Comparative evaluation and robustness analysis. The framework is examined through three simulated industrial supplier selection cases involving electric-vehicle battery cells, organic-cotton fabric and compostable packaging. The evaluation includes comparisons with existing measures, validation using held-out samples, ablation experiments and sensitivity analysis. These experiments examine the contribution of data-driven sub-attribute selection and the stability of supplier rankings under different modelling assumptions.

The study contributes to industrial intelligence research by addressing the relationship between predictive analytics, decision transparency and uncertainty representation in supplier selection. Unlike approaches that rely exclusively on model predictions or expert-defined evaluation criteria, the proposed framework uses machine learning explanations to structure an uncertainty-aware decision model. The numerical experiments are intended to establish the behaviour and internal validity of the proposed procedure under controlled conditions. Its effectiveness in operational procurement environments will require further examination using real industrial supplier records.

The remainder of the paper is organised as follows. Section 2 reviews related research and identifies the remaining methodological issues. Section 3 presents the mathematical preliminaries. Section 4 develops the proposed distance and similarity measures and examines their theoretical properties. Section 5 describes the XAI-based decision framework. Section 6 introduces the industrial supplier selection cases, while Sections 7 and 8 present the validation and sensitivity analyses. Section 9 discusses the findings and limitations, and Section 10 concludes the paper.

2 Literature Review

2.1 Neutrosophic and Hypersoft Structures for Uncertain Decision-Making

The representation of uncertain and incomplete information has received considerable attention in multi-criteria decision-making. Fuzzy set theory provides the basis for expressing partial membership [8], while intuitionistic fuzzy sets distinguish membership from non-membership [9]. Neutrosophic sets extend these concepts by introducing truth, indeterminacy and falsity as separate components [10]. Their interval-valued extension allows decision makers to represent assessments using lower and upper bounds, making it possible to describe imprecise evidence without assigning a single numerical value [11].

Soft set theory provides a complementary approach to parameter-based uncertainty modelling [12]. Neutrosophic soft sets combine parameterisation with the three neutrosophic components [13], and interval-valued neutrosophic soft sets further accommodate assessments expressed as intervals [14]. Hypersoft sets extend conventional soft sets by replacing individual parameters with combinations of sub-attribute values [15]. This distinction is important in supplier evaluation, where broad criteria such as environmental performance or operational reliability consist of several measurable characteristics that may influence a purchasing decision differently.

Subsequent developments have expanded the modelling capabilities of neutrosophic hypersoft structures. Aggregation operators have been introduced to combine uncertain evaluations [26], and hypersoft versions of multi-criteria ranking procedures have been investigated [27]. The m -Polar fuzzy set formulation allows several membership assessments to be associated with the same element [28]. Building on these developments, Saqlain and Xin [16] defined IVNHSS and their m -Polar extensions. Their approach provides a flexible representation for decision problems involving several evaluators, sources or assessment dimensions.

These structures are relevant to industrial procurement because information is rarely uniform across departments or evaluation periods. A procurement unit may have relatively precise cost information but limited knowledge of a supplier's environmental practices, whereas a sustainability department may have access to more detailed environmental assessments. Representing such differences through separate poles and interval-valued evaluations allows the decision model to retain information that would otherwise be lost through premature aggregation.

Nevertheless, uncertainty representation alone does not determine how alternatives should be compared. A practical intelligent decision system also requires suitable operators for measuring differences between evaluations and translating those differences into supplier rankings. The mathematical properties of such operators are therefore central to the reliability of the resulting decision procedure.

2.2 Distance and Similarity Measures in Neutrosophic Decision Models

Distance and similarity measures provide a mathematical basis for comparing uncertain assessments. In supplier selection, these measures are commonly used to evaluate how closely each supplier approaches an ideal profile or how strongly its characteristics differ from those of competing alternatives. The general principle of ranking alternatives according to their distances from ideal solutions is well established in multi-attribute decision-making [29].

Within neutrosophic modelling, Broumi and Smarandache [18] investigated similarity measures for neutrosophic sets, while Ye [19] developed vector-based similarity measures for simplified neutrosophic information. Mondal and Pramanik [20] introduced a tangent similarity measure, which was subsequently considered in the context of neutrosophic hypersoft structures by Saqlain et al. [21]. These contributions established several ways of comparing evaluations containing truth, indeterminacy and falsity information.

More recently, Saqlain et al. [17] developed distance and similarity measures for m -Polar IVNHSS and investigated their application to decision-making with a machine learning component. This work is particularly relevant because it demonstrates that similarity-based decision procedures can be constructed directly for the m -Polar interval-valued hypersoft setting. It also establishes an important point of comparison for further methodological developments.

Despite these contributions, the mathematical design of similarity-based models remains an important issue. Existing measures commonly employ specific functional forms, including absolute differences, Euclidean distances, vector similarity and trigonometric transformations. Their use in a particular decision problem does not automatically establish that every transformation preserves the properties of a metric. In particular, non-negativity, symmetry, identity of indiscernibles and the triangle inequality must be considered when a function is intended to represent a metric distance.

This distinction matters in industrial intelligent decision systems. A ranking procedure based solely on distance from an ideal profile may produce an ordering even when the underlying comparison function does not satisfy all metric properties. However, applications involving clustering, agreement analysis or repeated comparisons between supplier profiles may require stronger mathematical consistency. Consequently, identifying a general class of admissible transformations is more useful than introducing additional functional forms without a common theoretical basis.

The present study addresses this issue through concave generator functions. Rather than replacing established similarity-based decision models, it investigates conditions under which weighted transformations of interval endpoint differences produce mathematically valid distance measures. The proposed construction also allows different responses to small and large deviations from an ideal supplier profile. This provides a theoretical basis for selecting similarity functions in uncertainty-aware industrial decision applications.

2.3 Intelligent Supplier Selection and Explainable Artificial Intelligence

Sustainable supplier selection has traditionally been addressed through multi-criteria decision-making, where alternatives are assessed according to economic, environmental and social criteria. Reviews of green supplier evaluation have documented the extensive use of weighting methods, fuzzy approaches and distance-based ranking procedures [1]. More recent research has examined how AI, supply chain resilience and sustainability considerations can be incorporated into supplier selection models [30].

The development of Industry 4.0 and data-driven procurement has encouraged the use of machine learning to analyse historical supplier information. Studies of AI adoption in purchasing and supply management indicate that intelligent analytical tools can support supplier evaluation, procurement planning and other purchasing activities, although implementation remains uneven across organisations [3, 5]. The systematic review by Gidiagba et al. [4] further examined machine learning applications in sustainable supplier selection, including their roles in criteria identification, evaluation and ranking. Recent research has also applied supervised machine learning to supplier performance evaluation and risk profiling, demonstrating its relevance to data-driven supply chain decision-making [31].

A central issue in these applications is the interpretability of machine learning predictions. Models trained on supplier performance data may identify complex relationships between input characteristics and historical outcomes, but procurement managers still need explanations that can be examined in relation to organisational priorities. This is particularly important where purchasing decisions involve environmental compliance, labour practices or long-term operational commitments. Research on XAI in supply chain management has identified limited explainability as a significant obstacle to the wider adoption of intelligent analytical methods [7].

Shapley-value analysis provides one approach to explaining predictive models. Originally introduced in cooperative game theory [22], Shapley values were subsequently adapted to explain individual machine learning predictions [23]. The interventional formulation considered by Janzing et al. [24] provides a framework for examining feature contributions under a specified intervention-based value function. Gradient boosting [25] offers a suitable predictive model for structured supplier data, while Shapley attribution allows the contribution of individual supplier characteristics to be examined at both local and global levels.

The integration of machine learning and multi-criteria decision-making has also been investigated directly. Abdulla and Baryannis [6] proposed an explainable supplier selection framework combining data-driven learning with an interpretable decision procedure. Their study demonstrated the relevance of retaining transparent multi-criteria ranking while using machine learning to manage the complexity of supplier information. Recent research

has also combined machine learning with multi-criteria evaluation and optimisation to support supplier selection and order allocation under uncertainty [32].

These studies show that combining predictive learning with interpretable multi-criteria decision-making is an established research direction. The remaining question is how feature attribution can be incorporated into a decision structure that also represents multiple sources of interval-valued uncertainty. The present study addresses this question by using Shapley values to select one relevant sub-attribute from each evaluation category, derive criterion weights and support candidate screening. The selected attributes are subsequently evaluated within the m -Polar IVNHSS framework.

An important distinction is that Shapley values are used here as measures of predictive feature contribution rather than as direct evidence of causal influence. The framework therefore provides an interpretable means of structuring supplier evaluations from historical performance patterns, while the mathematical distance measures address uncertainty in the subsequent ranking process.

2.4 Research Gaps and Positioning of the Present Study

The preceding literature indicates that uncertainty modelling, similarity-based decision-making and explainable machine learning have developed into substantial research areas. Their combination is particularly relevant to intelligent industrial procurement, where data-driven recommendations must remain understandable and account for uncertain assessments. Nevertheless, three methodological issues motivate the present study.

First, the general mathematical construction of distance measures remains insufficiently developed for m -Polar IVNHSS. Existing studies have proposed individual distance or similarity functions, including measures specifically designed for multi-polar interval-valued neutrosophic hypersoft structures [17]. However, a unified class of transformations with explicit conditions for preserving metric properties remains a useful methodological development. The present study investigates this issue through concave generator functions and examines the mathematical properties of the resulting measures.

Second, the relationship between predictive feature importance and uncertainty-aware supplier evaluation requires further investigation. Machine learning and interpretable multi-criteria decision-making have already been combined in supplier selection [6, 32]. However, selecting sub-attributes and determining their weights from Shapley attributions within an m -Polar IVNHSS representation offers a more specific integration of predictive explanations and interval-valued multi-polar assessment. The proposed framework investigates whether this structure can provide an interpretable connection between historical supplier performance and uncertainty-aware ranking.

Third, the separate contributions of feature selection, weighting and similarity function design need to be distinguished. Sustainable supplier evaluation often involves several interacting modelling decisions, and changes in the selected criteria or weights can affect the resulting rankings. Consequently, evaluating the complete framework alone is insufficient to establish which components account for its performance. The present study uses held-out validation, ablation experiments and sensitivity analysis to examine these contributions separately.

The study is therefore positioned at the intersection of explainable machine learning, uncertainty-aware multi-criteria decision-making and industrial intelligence. Its primary contribution is the integration of mathematically constrained similarity measures with data-driven decision structuring, rather than the initial introduction of similarity measures or machine learning into neutrosophic supplier evaluation. The three simulated industrial cases provide controlled evidence concerning the behaviour of the proposed framework, while the limitations associated with synthetic data are retained in interpreting its practical significance.

3 Preliminaries

This section introduces the mathematical concepts and notation required for the proposed uncertainty-aware decision framework. In industrial supplier evaluation, alternatives are assessed using multiple criteria, each of which may contain several sub-attributes. Evaluations may also differ across organisational departments, planning horizons or information sources. The m -Polar IVNHSS provides a representation for these assessments.

Let $U = \{u_1, \dots, u_N\}$ be a finite universe of alternatives, and let $P(U)$ denote its power set. Consider $b \geq 1$ attributes, $L_1, \dots, L_b$, with corresponding nonempty sub-attribute sets $L_1^a, \dots, L_b^z$, assumed pairwise disjoint. Their Cartesian product is

$$\Lambda = L_1^a \times \dots \times L_b^z$$

An element $l = (l_1, \dots, l_b) \in \Lambda$ represents a tuple containing one selected sub-attribute from each attribute category.

Definition 3.1 (Hypersoft set [15]). A hypersoft set over U is a pair (F, Λ) , where

$$F : \Lambda \rightarrow P(U)$$

This construction allows an evaluation to depend on combinations of sub-attribute values rather than on individual attributes alone.

Definition 3.2 (*m*-Polar IVNHSS [16]). An *m*-Polar IVNHSS is a pair (F, Λ) in which each alternative is associated with interval-valued truth, indeterminacy and falsity assessments across *m* poles. For each $l \in \Lambda$,

$$F(l) = \left\{ \langle u, \tilde{T}_l^p(u), \tilde{I}_l^p(u), \tilde{F}_l^p(u) \rangle : u \in U, p = 1, \dots, m \right\} \quad (1)$$

where,

$$\begin{aligned} \tilde{T}_l^p(u) &= [T_l^{(p-)}(u), T_l^{(p+)}(u)] \\ \tilde{I}_l^p(u) &= [I_l^{(p-)}(u), I_l^{(p+)}(u)] \\ \tilde{F}_l^p(u) &= [F_l^{(p-)}(u), F_l^{(p+)}(u)] \end{aligned}$$

All intervals lie within $[0,1]$, with each lower endpoint not exceeding its corresponding upper endpoint.

Remark 3.1 (Pole-sum constraint). The original formulation in the study [16] restricts the sums of the upper truth, indeterminacy and falsity bounds across poles to at most one for each component. This convention is appropriate when the poles partition a common unit of evidence. In industrial decision problems, however, poles may represent independent evaluators, planning horizons or evidence sources. Accordingly, the present framework adopts independent interval constraints for each pole, consistent with the *m*-Polar representation in the study [28]. The mathematical results in Section 4 remain valid under either convention because all interval endpoints belong to $[0,1]$.

Notation. For a selected sub-attribute tuple l , let Ψ denote an *m*-Polar IVNHSS evaluation. Its component-wise representation for alternative u is written as

$$\Psi(u) = \left(X_{j,\Psi}^{(p\pm)}(u) \right)$$

where, $j = 1, \dots, n$ indexes the selected sub-attributes, $n = b$, $p = 1, \dots, m$ indexes the poles, $X \in \{T, I, F\}$, and the signs $-$ and $+$ indicate interval endpoints.

In the supplier selection applications, u represents a supplier, j identifies a selected evaluation criterion, and p represents an organisational unit, planning horizon or evidence source. The notation $m\text{IVNHSS}(U)$ denotes the family of admissible evaluation arrays defined on a common sub-attribute tuple and pole structure. This common indexing is required for component-wise comparison.

4 Proposed Distance and Similarity Measures

Reliable supplier ranking requires a consistent means of comparing uncertain assessments with an ideal supplier profile. Conventional distance functions provide useful reference measures, but different transformations of interval discrepancies may respond differently to small and large deviations. This section introduces a class of concave generators for constructing weighted distances and corresponding similarity measures on *m*-Polar IVNHSS. The construction is intended to provide mathematical consistency while allowing the decision maker to adjust sensitivity to deviations from the ideal.

4.1 Concave Generators

Definition 4.1 (Generator class $\mathcal{G}$). A function

$$\varphi : [0, 1] \rightarrow [0, 1]$$

belongs to the class $\mathcal{G}$ if it satisfies the following conditions:

- (G1) $\varphi(0) = 0, \quad \varphi(1) = 1$
- (G2) φ is strictly increasing
- (G3) φ is concave

The identity function $\varphi(x) = x$, corresponding to the Hamming transformation, belongs to $\mathcal{G}$ and is its only linear member. Four nonlinear generators are considered below.

Definition 4.2 (Proposed generators). For $x \in [0, 1]$ and $\lambda > 0$, define

$$\varphi_{\sin}(x) = \sin\left(\frac{\pi x}{2}\right) \quad (2)$$

$$\varphi_{\exp}^{\lambda}(x) = \frac{1 - e^{-\lambda x}}{1 - e^{-\lambda}} \quad (3)$$

$$\varphi_{\tanh}^\lambda(x) = \frac{\tanh(\lambda x)}{\tanh(\lambda)} \quad (4)$$

$$\varphi_{hyb}^\lambda(x) = \sqrt{\varphi_{\sin}(x)\varphi_{\exp}^\lambda(x)} \quad (5)$$

The sine generator provides a fixed nonlinear transformation, whereas the exponential and hyperbolic-tangent generators allow their sensitivity to be adjusted through λ . The hybrid generator combines the sine and exponential transformations.

Lemma 4.1 Each generator in Definition 4.2 belongs to $\mathcal{G}$.

Proof. All four functions satisfy the endpoint conditions and are strictly increasing on $[0,1]$. The sine, exponential and hyperbolic-tangent generators are concave, as follows directly from their first and second derivatives. For the hybrid generator, the geometric mean is concave and nondecreasing in each argument on the nonnegative domain. Since both constituent functions are nonnegative, increasing and concave, their geometric-mean composition is also concave. Thus, all four generators satisfy conditions (G1)–(G3).

Lemma 4.2 (Subadditivity)

If $\varphi \in \mathcal{G}$, then $\varphi(x+y) \leq \varphi(x) + \varphi(y)$, whenever $x, y, x+y \in [0,1]$, and $\varphi(x) + \varphi(y) \geq 1$ whenever $x, y \in [0,1]$ with $x+y \geq 1$.

Proof. Let $x, y \geq 0$ and $x+y \leq 1$. For $x+y > 0$, concavity and $\varphi(0) = 0$ imply

$$\varphi(x) \geq \frac{x}{x+y} \varphi(x+y)$$

and

$$\varphi(y) \geq \frac{y}{x+y} \varphi(x+y)$$

Adding these inequalities gives

$$\varphi(x) + \varphi(y) \geq \varphi(x+y)$$

The result is immediate when $x = y = 0$. Furthermore, concavity and the endpoint conditions imply

$$\varphi(t) \geq t, \quad t \in [0,1]$$

Consequently, when $x+y \geq 1$,

$$\varphi(x) + \varphi(y) \geq x+y \geq 1$$

Both statements follow.

Definition 4.3 (Small-Discrepancy Sensitivity)

For $\varphi \in \mathcal{G}$ differentiable at zero, define

$$\sigma(\varphi) = \varphi'(0) \quad (6)$$

By concavity and the endpoint conditions, the graph of φ lies above the chord joining $(0,0)$ and $(1,1)$. Therefore,

$$\sigma(\varphi) \geq 1$$

Equality holds only for the identity generator, since the derivative of a concave function is nonincreasing and its average slope over $[0,1]$ equals one.

The sensitivities of the proposed generators are

$$\sigma(\varphi_{\sin}) = \frac{\pi}{2} \approx 1.571$$

$$\sigma(\varphi_{\exp}^\lambda) = \frac{\lambda}{1 - e^{-\lambda}}$$

$$\sigma(\varphi_{\tanh}^\lambda) = \frac{\lambda}{\tanh(\lambda)}$$

and

$$\sigma(\varphi_{hyb}^\lambda) = \sqrt{\sigma(\varphi_{\sin})\sigma(\varphi_{\exp}^\lambda)}$$

For $\lambda = 1, 2, 5$, the exponential generator has sensitivities of approximately 1.582, 2.313 and 5.034, respectively, while those of the hyperbolic-tangent generator are approximately 1.313, 2.075 and 5.000. The hybrid generator has a sensitivity of approximately 1.907 at $\lambda = 2$.

The parameter λ controls the response to small discrepancies. Larger values increase the initial sensitivity of the parameterised generators. As λ approaches zero, the exponential and hyperbolic-tangent generators approach the Hamming transformation, whereas the hybrid generator approaches the geometric mean of the sine and identity transformations.

In industrial supplier evaluation, this parameter allows decision makers to examine how different levels of sensitivity to deviations affect supplier rankings. Figure 1 illustrates the proposed generators alongside the Hamming and tangent transformations.

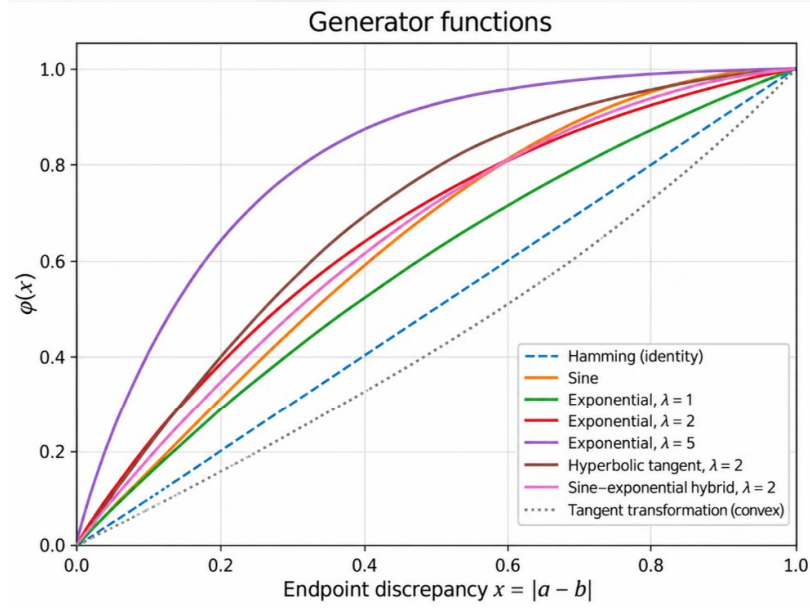


Figure 1. Proposed concave generators compared with the Hamming (identity) transformation and a convex tangent transformation

4.2 Distance Measures on Multi-Polar Interval-Valued Neutrosophic Hypersoft Sets

Let $\Psi, \Omega \in mIVNHSS(U)$ represent two evaluations defined over the same selected sub-attribute tuple and pole structure. Each evaluation is expressed as a component-wise interval-valued array, allowing corresponding supplier characteristics to be compared directly.

Let

$$w = (w_1, \dots, w_n), \quad w_j \geq 0, \quad \sum_{j=1}^n w_j = 1$$

denote the attribute weights, and

$$\omega = (\omega_1, \dots, \omega_m), \quad \omega_p \geq 0, \quad \sum_{p=1}^m \omega_p = 1$$

denote the pole weights.

Here, w_j represents the relative importance of the j -th selected sub-attribute, while ω_p represents the contribution of the p -th decision-making unit, planning horizon or information source.

For each alternative $u \in U$, define the corresponding endpoint discrepancies as

$$\Delta_{X,j}^{(p\pm)}(u) = \left| X_{j,\Psi}^{(p\pm)}(u) - X_{j,\Omega}^{(p\pm)}(u) \right|$$

where,

$$X \in \{T, I, F\}, \quad \Delta_{X,j}^{(p\pm)}(u) \in [0, 1]$$

These discrepancies quantify differences between corresponding truth, indeterminacy and falsity interval endpoints.

Definition 4.4 (Weighted φ -distance: averaging form). For $\varphi \in \mathcal{G}$, define

$$D_\varphi(\Psi, \Omega) = \frac{1}{6N} \sum_{u \in U} \sum_{j=1}^n w_j \sum_{p=1}^m \omega_p \sum_{X \in \{T, I, F\}} \left[\varphi(\Delta_{X,j}^{(p-)}(u)) + \varphi(\Delta_{X,j}^{(p+)}(u)) \right] \quad (7)$$

This measure combines the transformed discrepancies of all interval endpoints through nonnegative attribute and pole weights. The normalisation ensures that

$$0 \leq D_\varphi(\Psi, \Omega) \leq 1$$

In industrial supplier evaluation, the averaging form provides an overall measure of disagreement between two uncertain supplier profiles while accounting for the relative importance of the selected criteria and information sources.

Definition 4.5 (Weighted φ -distance: Hausdorff form). For $\varphi \in \mathcal{G}$, define

$$D_{\varphi}^H(\Psi, \Omega) = \frac{1}{3N} \sum_{u \in U} \sum_{j=1}^n w_j \sum_{p=1}^m \omega_p \sum_{X \in \{T, I, F\}} \varphi \left(\max \left\{ \Delta_{X,j}^{(p-)}(u), \Delta_{X,j}^{(p+)}(u) \right\} \right) \quad (8)$$

The Hausdorff form considers the larger discrepancy between corresponding interval endpoints. Unlike the averaging form, it assigns the same component-level penalty when one endpoint exhibits a substantial deviation, regardless of whether the other endpoint differs by a similar amount.

This property is relevant to industrial decision-making when uncertainty at either end of an assessment interval may affect supplier evaluation. The averaging form reflects overall interval differences, whereas the Hausdorff form gives greater emphasis to the largest endpoint deviation.

Definition 4.6 (Similarity measures). The corresponding similarity measures are defined as

$$S_{\varphi}(\Psi, \Omega) = 1 - D_{\varphi}(\Psi, \Omega) \quad (9)$$

and

$$S_{\varphi}^H(\Psi, \Omega) = 1 - D_{\varphi}^H(\Psi, \Omega) \quad (10)$$

Both measures satisfy

$$0 \leq S_{\varphi}(\Psi, \Omega) \leq 1$$

and

$$0 \leq S_{\varphi}^H(\Psi, \Omega) \leq 1$$

A larger similarity value indicates a smaller distance between the corresponding evaluations.

In the proposed intelligent supplier decision framework, the similarity between each candidate supplier and the ideal supplier profile provides the basis for ranking alternatives. The selected generator determines how discrepancies are transformed, while the attribute and pole weights determine their relative contributions.

4.3 Mathematical Properties

This section establishes the metric and similarity properties of the proposed measures on a common, component-wise interval-valued evaluation space. All comparisons below use the same sub-attribute and pole indices and fixed, normalised nonnegative weights.

Theorem 4.1 (Metric axioms). For each $\varphi \in \mathcal{G}$, the functions D_{φ} and D_{φ}^H satisfy, for all $\Psi, \Omega, \Theta \in mIVNHSS(U)$:

(M1) Boundedness:

$$0 \leq D(\Psi, \Omega) \leq 1$$

(M2) Symmetry:

$$D(\Psi, \Omega) = D(\Omega, \Psi)$$

(M3) Identity of indiscernibles: if all attribute and pole weights are strictly positive,

$$D(\Psi, \Omega) = 0 \iff \Psi = \Omega$$

(M4) Triangle inequality:

$$D(\Psi, \Theta) \leq D(\Psi, \Omega) + D(\Omega, \Theta)$$

Accordingly, both functions are bounded pseudometrics for nonnegative admissible weights and metrics for strictly positive weights.

Proof. Every endpoint discrepancy lies in $[0, 1]$, and $0 \leq \varphi(x) \leq 1$. Since the weights are normalised, (M1) follows. Absolute differences are symmetric, proving (M2). Because φ is strictly increasing and $\varphi(0) = 0$, each transformed discrepancy vanishes exactly when its endpoints agree; positive weights therefore imply (M3).

For endpoints $a, b, c \in [0, 1]$, put $r = |a - b|$ and $s = |b - c|$. Then $|a - c| \leq r + s$. If $r + s \leq 1$, monotonicity and Lemma 4.2 give

$$\varphi(|a - c|) \leq \varphi(r + s) \leq \varphi(r) + \varphi(s)$$

If $r + s > 1$, Lemma 4.2 instead gives

$$\varphi(|a - c|) \leq 1 \leq \varphi(r) + \varphi(s)$$

Thus the transformed scalar discrepancies obey the triangle inequality, which is preserved by nonnegative weighted summation in D_φ . For the Hausdorff-type form, the endpoint maximum satisfies

$$\max_{k=1,2} |a_k - c_k| \leq \max_{k=1,2} |a_k - b_k| + \max_{k=1,2} |b_k - c_k|$$

Applying the same generator argument and weighted summation establishes (M4) for D_φ^H .

Theorem 4.2 (Similarity properties). The similarities $S_\varphi = 1 - D_\varphi$ and $S_\varphi^H = 1 - D_\varphi^H$ satisfy:

(S1) $0 \leq S(\Psi, \Omega) \leq 1$

(S2) $S(\Psi, \Omega) = S(\Omega, \Psi)$

(S3) $S(\Psi, \Omega) = 1 \iff \Psi = \Omega$ when all weights are strictly positive

(S4) if every endpoint of Ω lies between the corresponding endpoints of Ψ and Θ , then

$$S(\Psi, \Theta) \leq \min\{S(\Psi, \Omega), S(\Omega, \Theta)\}$$

Proof. Properties (S1)–(S3) follow from Theorem 4.1. Under the component-wise betweenness assumption in (S4), corresponding endpoints a, b, c satisfy $|a - c| \geq \max\{|a - b|, |b - c|\}$. Monotonicity of φ , the endpoint maximum and nonnegative weighted summation imply

$$D(\Psi, \Theta) \geq \max\{D(\Psi, \Omega), D(\Omega, \Theta)\}$$

Substituting $S = 1 - D$ proves (S4). This betweenness condition is required; it must not be replaced without justification by a different neutrosophic set-inclusion convention.

Proposition 4.3 (Ordering and bounds). For $\varphi \in \mathcal{G}$ differentiable at zero with finite $\sigma(\varphi) = \varphi'(0)$,

$$D_{\text{Hamming}} \leq D_\varphi \leq \min\{1, \sigma(\varphi) D_{\text{Hamming}}\} \quad (11)$$

and

$$D_\varphi \leq D_\varphi^H \leq 2D_\varphi \quad (12)$$

Proof. Concavity and the endpoint conditions give

$$x \leq \varphi(x) \leq \sigma(\varphi)x \quad 0 \leq x \leq 1$$

Applying this bound to each endpoint discrepancy and summing with nonnegative weights yields the first inequality. For $r, s \geq 0$,

$$\frac{r+s}{2} \leq \max\{r, s\} \leq r+s$$

Apply this with $r = \varphi(\Delta^-)$ and $s = \varphi(\Delta^+)$, using that $\varphi(\max\{\Delta^-, \Delta^+\}) = \max\{r, s\}$. Weighted summation proves the second inequality.

Proposition 4.4 (The tangent transformation does not generate a metric). Consider the tangent-transformed endpoint distance obtained by substituting

$$\varphi_{\tan}(x) = \tan\left(\frac{\pi x}{4}\right), \quad x \in [0, 1]$$

into Definition 4.4 or 4.5. This transformation is convex and does not generally satisfy the triangle inequality.

Proof. For $x \in (0, 1]$,

$$\varphi_{\tan}''(x) = 2 \left(\frac{\pi}{4}\right)^2 \tan\left(\frac{\pi x}{4}\right) \sec^2\left(\frac{\pi x}{4}\right) > 0$$

Take three corresponding scalar values $a = 0, b = \frac{1}{2}, c = 1$. Then

$$\varphi_{\tan}(|a - c|) = 1 > 2 \tan\left(\frac{\pi}{8}\right) \approx 0.8284$$

A valid embedding uses degenerate intervals $[a, a], [b, b], [c, c]$ in one component of three evaluation arrays, with every other component identical and with a positive weight on the varying component. Its positive common normalisation factor preserves the strict inequality, so

$$D(\Psi, \Theta) > D(\Psi, \Omega) + D(\Omega, \Theta)$$

This conclusion applies to the tangent-transformed distance defined here, not automatically to every tangent-based similarity in previous studies [20, 21].

Proposition 4.5 (Reductions). The proposed measures admit the following restricted forms: (a) $m = 1$ gives interval-valued neutrosophic hypersoft evaluation distances [18]; (b) if every interval is degenerate, $X^{(p-)} = X^{(p+)}$, the measures reduce to an m -Polar single-valued form, with $D_\varphi = D_\varphi^H$; (c) combining $m = 1$ with degenerate intervals gives a single-valued neutrosophic hypersoft form, whose identity-generator case is a normalised Hamming-type distance [14]; and (d) $b = 1$ gives the corresponding single-attribute soft-set evaluation form.

Proof. The cases follow by fixing the pole or attribute indices or equating the two endpoints. These restrictions preserve the normalised weighted construction and its metric properties on the corresponding restricted spaces, subject to positive weights for identity of indiscernibles.

These results establish metric consistency for the proposed component-wise comparison rules. Section 5 uses the resulting similarities together with gradient-boosting predictions and Shapley-based feature selection to rank suppliers under uncertain assessments.

5 Explainable Artificial Intelligence-Based Intelligent Supplier Decision Framework

The proposed framework integrates predictive learning, feature attribution and uncertainty-aware similarity measures to support intelligent supplier selection. Industrial procurement decisions often involve numerous evaluation criteria, but not all sub-attributes contribute equally to supplier performance. Moreover, different departments or information sources may provide assessments with varying degrees of uncertainty. The framework addresses these issues through two connected stages: data-driven decision structuring and interval-valued supplier ranking.

In the first stage, a gradient-boosting classifier was used to analyse historical supplier performance patterns. Shapley-value explanations were then employed to identify relevant sub-attributes, derive criterion weights and support candidate screening. In the second stage, the selected suppliers were represented using m -Polar IVNHSS evaluations and ranked according to the similarity measures developed in Section 4. The resulting procedure combines predictive information with explicit uncertainty representation, while allowing decision makers to examine and revise the choices suggested by the model.

5.1 Shapley-Based Feature Attribution

Let

$$f : [0, 1]^q \rightarrow [0, 1]$$

denote a fitted gradient-boosting classifier, where q is the number of candidate sub-attributes. For an input vector x , the output $f(x)$ represents the predicted probability of a successful supplier engagement.

To explain individual predictions, the interventional Shapley formulation was adopted [22–24]. For a feature coalition

$$S \subseteq \{1, \dots, q\}$$

and a background sample Z , the value function is defined as

$$v_x(S) = E_{z \sim Z} [f(x_S, z_{\bar{S}})] \quad (13)$$

where, x_S contains the observed values of the features in S , and $z_{\bar{S}}$ supplies the remaining values from the background distribution.

The Shapley attribution of feature i is

$$\phi_i(x) = \sum_{S \subseteq \{1, \dots, q\} \setminus \{i\}} \frac{|S|!(q - |S| - 1)!}{q!} [v_x(S \cup \{i\}) - v_x(S)] \quad (14)$$

This formulation distributes the difference between a prediction and its reference value among the input features. It satisfies the established Shapley attribution properties, including efficiency, symmetry, the dummy property and additivity [22, 23]. The interventional formulation follows the feature-relevance interpretation discussed in the study [24].

In all three case studies, $q = 12$, allowing the $2^{12} = 4,096$ feature coalitions to be enumerated without coalition-sampling approximation. The resulting attributions are exact with respect to the specified empirical background distribution and value function.

The global importance of feature i was calculated as the mean absolute Shapley attribution over an explanation sample E :

$$\bar{\phi}_i = \frac{1}{|E|} \sum_{x \in E} |\phi_i(x)| \quad (15)$$

This quantity measures the average contribution of a feature to the magnitude of model predictions, rather than its causal effect on supplier performance. In the proposed industrial decision framework, it provides a data-driven basis for selecting evaluation criteria and examining their relative predictive importance.

5.2 Decision Structuring and Supplier Ranking

The Shapley attributions were used to construct the supplier evaluation model through three main procedures: sub-attribute selection, criterion weighting, and candidate screening. The retained suppliers were subsequently evaluated using the m -Polar IVNHSS similarity measures developed in Section 4.

Sub-attribute selection. For each attribute category, the candidate sub-attribute with the greatest global Shapley importance was selected. Let A_j denote the set of candidate features associated with attribute j . The selected feature is

$$i_j^* = \arg \max_{i \in A_j} \bar{\phi}_i \quad (16)$$

The selected features form the evaluation tuple

$$l^* = (i_1^*, \dots, i_b^*)$$

This procedure retains one representative sub-attribute from each category, allowing the decision model to focus on characteristics that contribute most strongly to the predictive classifier. The selected tuple also defines the evaluation dimensions used in the subsequent uncertainty-aware assessment.

Criterion weighting. The global importance values of the selected sub-attributes were normalised to obtain their relative weights:

$$w_j = \frac{\bar{\phi}_{i_j^*}}{\sum_{k=1}^b \bar{\phi}_{i_k^*}} \quad (17)$$

The proportion of total feature importance represented by the selected tuple was calculated as

$$\text{Coverage} = \frac{\sum_{j=1}^b \bar{\phi}_{i_j^*}}{\sum_{i=1}^q \bar{\phi}_i} \quad (18)$$

These weights reflect the relative predictive contributions of the selected features. They provide a data-driven basis for structuring the evaluation but do not necessarily represent the preferences of procurement managers or other decision-making units.

Pole weighting. Each pole represents an organisational unit, planning horizon, or evidence source. The pole weights were determined in proportion to the reciprocal of the corresponding evaluation interval widths and normalised to sum to one. Under this rule, narrower evaluation intervals received greater weights, reflecting the assumed higher precision of the associated assessments.

Candidate screening and ranking. The gradient-boosting classifier was used to estimate the success probability of each candidate supplier. The candidates were ordered by their predicted probabilities, and the top K suppliers were retained for detailed evaluation.

For each retained supplier, interval-valued truth, indeterminacy, and falsity assessments were constructed across the selected sub-attributes and poles. The resulting m -Polar IVNHSS profiles were compared with an ideal supplier profile using the distance and similarity measures defined in Section 4. Suppliers were ranked in descending order of similarity to the ideal.

The complete decision procedure therefore comprised predictive modelling, Shapley attribution, sub-attribute selection, criterion weighting, candidate screening, interval-valued evaluation, and similarity-based ranking. Figure 2 illustrates the framework.

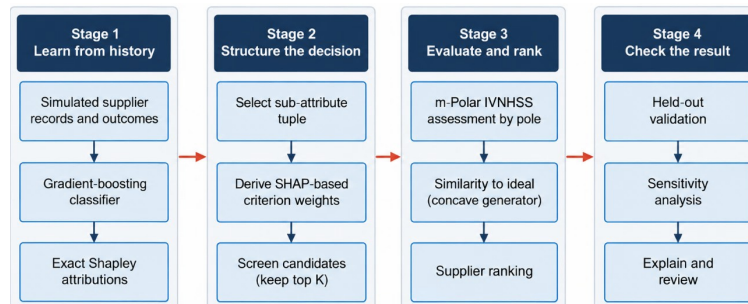


Figure 2. Architecture of the proposed XAI-based intelligent supplier decision framework, integrating predictive modelling, Shapley attribution, uncertainty representation, and supplier ranking

Note: XAI = explainable artificial intelligence; SHAP = SHapley Additive exPlanations; m -Polar IVNHSS = multi-Polar interval-valued neutrosophic hypersoft set.

The distinction between the predictive and similarity-based stages is important. The classifier identifies informative evaluation characteristics and screens the candidates, whereas the m -Polar IVNHSS measures determine their final ranking under uncertain assessments. This integration provides an interpretable approach to industrial supplier selection while allowing decision makers to review the selected criteria and adjust the evaluation assumptions when necessary.

6 Experimental Design and Industrial Case Studies

6.1 Common Experimental Design

Three simulated industrial supplier selection cases were considered to examine the proposed framework under different sources of uncertainty. The cases involved electric-vehicle battery cells (case study1) (CS1), organic-cotton fabric (CS2), and compostable packaging (CS3). Although the industrial settings differed, the same predictive modelling and uncertainty-aware ranking procedures were applied throughout.

Each case contained four evaluation categories: Economic, Environmental, Social, and Operational. Three candidate sub-attributes were included in each category, giving a total of 12 input features. The simulated historical dataset comprised 600 supplier engagements with binary success outcomes. Eight candidate suppliers were considered in each case, and the five candidates with the highest predicted success probabilities were retained for detailed assessment.

Each case incorporated three poles, representing different sources or dimensions of uncertainty. In CS1, the poles corresponded to the Procurement Department, Sustainability Office, and Operations Unit. In CS2, they represented planning horizons of one year, three years, and at least five years. In CS3, they represented third-party audits, supplier self-assessments, and on-site inspections.

All evaluation criteria were oriented so that larger values indicated more favourable performance. Cost-type attributes were transformed using $s' = 1 - s$.

A gradient-boosting classifier was employed to estimate supplier success probabilities [25]. The model contained 250 trees with a maximum depth of 3, a learning rate of 0.05, and a subsampling rate of 0.80. Unless otherwise stated, the generator parameter was set to $\lambda = 2$.

The simulated supplier records were generated using a fixed, seeded process incorporating nonlinear relationships and an interaction between environmental and social characteristics. The use of synthetic data allowed the proposed method to be examined under controlled conditions without relying on confidential procurement records.

Shapley-value analysis was used to identify one sub-attribute from each evaluation category and derive the corresponding criterion weights. The retained suppliers were subsequently evaluated using m -Polar IVNHSS representations and ranked according to similarity to the ideal supplier profile. Figure 3 summarises the selected sub-attributes, criterion weights, pole weights, and supplier rankings for the three cases.

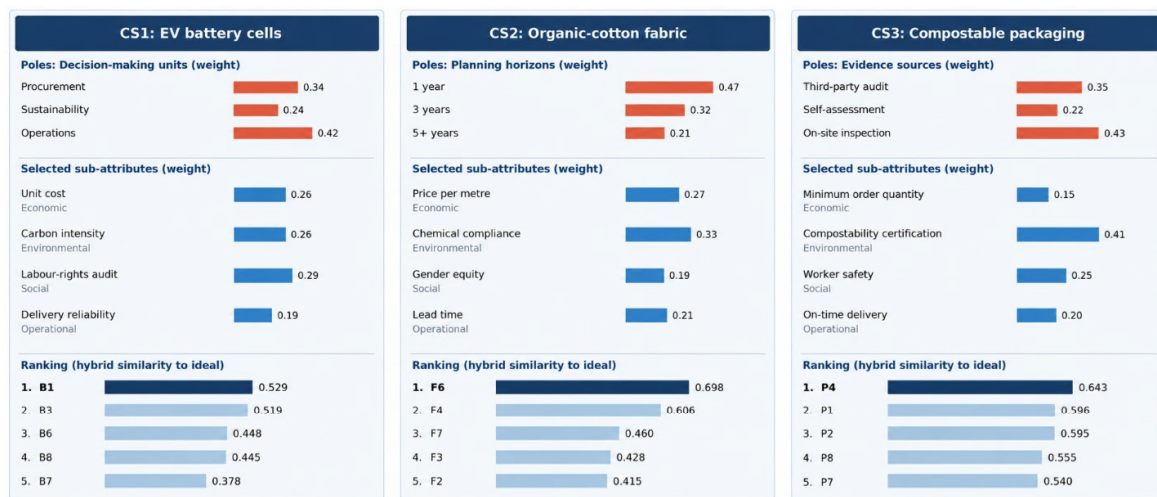


Figure 3. Comparison of the three simulated industrial supplier selection cases, showing pole weights, Shapley-selected sub-attributes, criterion weights and similarity-based rankings using the hybrid generator $\lambda = 2$

Note: CS = case study; EV = electric vehicle.

The experiments were designed to assess the mathematical and predictive behaviour of the framework. The results therefore provide controlled methodological evidence rather than validation of the framework in an operational industrial environment.

6.2 Case Study 1: Electric-Vehicle Battery Cell Suppliers

The first case examined the selection of a lithium-ion battery cell supplier for an automotive manufacturer. Supplier evaluation in this setting involves purchasing costs, environmental impacts, labour practices and delivery reliability. The three poles represented the Procurement Department, Sustainability Office and Operations Unit, allowing differences between organisational perspectives to be retained in the assessment.

The gradient-boosting classifier achieved a cross-validated area under the receiver operating characteristic curve (AUC) of 0.792 and an accuracy of 0.703, with a baseline success rate of 0.500. Shapley-value analysis identified four sub-attributes—Unit cost, Carbon intensity, Labour-rights audit score, and Delivery reliability—which together accounted for 62.6% of the total global feature importance (as shown in Figure 3).

Labour-rights audit score received the greatest relative weight among the selected criteria. This result reflected its predictive contribution in the simulated dataset and should not be interpreted as evidence that labour practices necessarily dominate supplier performance in actual battery manufacturing.

The initial screening excluded suppliers B2, B4 and B5, whose predicted success probabilities were 0.217, 0.151 and 0.312, respectively. The local Shapley explanations identified Delivery reliability as the largest negative contributor for suppliers B2 and B5, while Unit cost contributed most negatively to the prediction for B4. Such explanations illustrate how an intelligent procurement system can provide information about the characteristics associated with an unfavourable prediction, rather than reporting a score alone.

The five retained suppliers were subsequently evaluated using interval-valued truth, indeterminacy, and falsity assessments from the three decision-making units. These assessments were used to construct the m -Polar IVNHSS supplier profiles for similarity-based ranking. The Sustainability Office produced the widest intervals because its information about costs and delivery was less direct, whereas the Operations Unit produced the narrowest intervals. These differences were reflected in the pole weights shown in Figure 3.

Table 1 reports the similarity scores and corresponding rankings under the proposed and reference measures.

Table 1. Similarity-to-ideal scores and supplier rankings for case study (CS)1 ($\lambda = 2$)

Measure	B1	B3	B6	B7	B8
Hamming	0.6763 (1)	0.6653 (2)	0.5962 (4)	0.5327 (5)	0.6016 (3)
Euclidean	0.6050 (1)	0.5889 (2)	0.5153 (4)	0.4604 (5)	0.5310 (3)
Tangent (reference)	0.7303 (1)	0.7169 (2)	0.6519 (4)	0.5946 (5)	0.6617 (3)
Cosine (reference)	0.7187 (1)	0.7091 (2)	0.5898 (4)	0.4772 (5)	0.5978 (3)
Sine	0.5452 (1)	0.5391 (2)	0.4636 (3)	0.3889 (5)	0.4588 (4)
Exponential	0.5100 (1)	0.4962 (2)	0.4296 (3)	0.3665 (5)	0.4289 (4)
Hyperbolic tangent	0.4825 (1)	0.4720 (2)	0.4027 (3)	0.3356 (5)	0.3989 (4)
Sine–exponential hybrid	0.5285 (1)	0.5188 (2)	0.4476 (3)	0.3784 (5)	0.4448 (4)
Relative closeness (hybrid)	0.6355 (1)	0.6270 (2)	0.5736 (4)	0.5250 (5)	0.5770 (3)

Note: B1, B3, B6, B7, and B8 denote the five suppliers evaluated in CS1.

All four proposed generators produced the ranking $B1 \succ B3 \succ B6 \succ B8 \succ B7$. The Hamming, Euclidean, tangent, and cosine reference measures identified the same two leading suppliers but placed B8 above B6.

The difference was associated with the distribution of criterion-level discrepancies. Supplier B8 performed relatively well on unit cost but received less favourable assessments for carbon intensity and labour rights, whereas B6 showed more balanced performance across the selected criteria. The concave transformations altered the relative contributions of small and large discrepancies, resulting in a narrow advantage for B6. Under the sine–exponential hybrid measure, the similarity scores of B6 and B8 were 0.4476 and 0.4448, respectively, a difference of only 0.0028.

These results illustrate how the choice of similarity function can affect the ordering of closely ranked suppliers. However, the small difference between B6 and B8 should not be interpreted as evidence of a substantial difference in their expected performance.

6.3 Case Study 2: Organic-Cotton Fabric Suppliers

The second case considered the selection of an organic-cotton fabric supplier for an apparel manufacturer. The three poles represented planning horizons of one year, three years and at least five years. Longer planning horizons were assigned wider evaluation intervals to represent greater uncertainty about future supplier performance.

The gradient-boosting classifier achieved a cross-validated AUC of 0.682, indicating weaker predictive discrimination than in CS1. Shapley attribution selected Price per metre, Chemical compliance, Gender equity and Lead time, with total importance coverage of 0.428.

Within the Social category, Gender equity and Living-wage compliance had similar global importance values of 0.054 and 0.051, respectively. The difference was small and did not establish that one feature would consistently

outperform the other under alternative data samples. The original data-driven selection was retained to evaluate the specified procedure without manual intervention.

The screening stage removed suppliers F1, F5 and F8. All the examined similarity measures produced the same final ranking $F6 \succ F4 \succ F7 \succ F3 \succ F2$.

Supplier F6 performed favourably on three of the four selected evaluation criteria, explaining its consistent leading position. Unlike CS1, the ranking was not affected by the choice of generator (Figure 3).

This result suggests that the functional form of the similarity measure may have limited influence when the differences between alternatives are sufficiently clear. However, the relatively low AUC and modest feature-importance coverage indicate that the predictive explanations in this case should be interpreted cautiously.

6.4 Case Study 3: Compostable Packaging Suppliers

The third case examined supplier selection for certified-compostable packaging used by a food manufacturer. The three poles represented a third-party audit, supplier self-assessment and the buyer's on-site inspection.

The evaluation intervals were designed to reflect different levels of information precision. Supplier self-assessments were treated as the least precise source, while on-site inspections received the narrowest intervals.

The predictive classifier achieved a cross-validated AUC of 0.766. Shapley attribution selected Minimum order quantity, Compostability certification, Worker safety record and On-time delivery, with importance coverage of 0.515. Compostability certification accounted for approximately 41% of the total weight assigned to the selected criteria.

Suppliers P3, P5 and P6 were excluded during initial screening. The hybrid generator produced the ranking $P4 \succ P1 \succ P2 \succ P8 \succ P7$.

Supplier P4 ranked first under every measure. However, P1 and P2 differed only slightly, and the exponential and hyperbolic-tangent generators reversed their relative positions. Similar differences appeared between P7 and P8.

This case illustrates the influence of evidence precision and criterion importance on uncertainty-aware industrial supplier evaluation. It also indicates that close alternatives should not be distinguished solely on the basis of small numerical differences in similarity scores.

6.5 Cross-Case Comparison

Across the three simulated cases, all four proposed generators identified the same highest-ranked supplier at $\lambda = 2$. Differences between measures occurred mainly among alternatives with closely spaced similarity scores. The tangent and cosine reference measures reproduced the Hamming ordering in CS1 and CS2, while differences appeared among closely ranked suppliers in CS3. The sine, hyperbolic-tangent, and hybrid generators were reported to produce wider score ranges than Hamming. These findings indicate that nonlinear transformations affect the numerical separation of supplier profiles, although greater score separation does not necessarily imply higher predictive accuracy. The predictive discrimination of the resulting similarity scores is examined in Section 7.

7 Comparative Evaluation and Validation

The practical value of an intelligent supplier ranking method depends on whether its scores provide useful information about subsequent supplier performance. To examine this question, the proposed similarity measures were evaluated using held-out observations generated independently from the same simulation process as the training data.

For each case, 150 additional suppliers were generated. These observations were not used to train the classifier, calculate the Shapley attributions or construct the original candidate evaluation matrices. Each held-out supplier was represented using an m -Polar IVNHSS evaluation consistent with the corresponding case structure. Similarity to the ideal supplier profile was then calculated using the selected sub-attributes and XAI-derived weights.

The AUC was used to assess how well each scoring rule distinguished successful from unsuccessful supplier outcomes. Figure 4 compares the AUC results of the proposed similarity measures, reference methods, and two ablation configurations: the hybrid measure with equal criterion weights and the hybrid measure using the least important sub-attributes.

The hybrid similarity measure achieved AUC values of 0.802, 0.630 and 0.837 in CS1, CS2 and CS3, respectively. The corresponding values for the gradient-boosting classifier were 0.811, 0.710 and 0.848. The differences between the hybrid similarity measure and the classifier were therefore 0.009, 0.080 and 0.011 across the three cases. The hybrid measure approached the classifier's discrimination performance in CS1 and CS3, although the difference was more pronounced in CS2. These results are notable because the similarity-based decision model used only four selected sub-attributes rather than the complete set of twelve candidate features.

Across the proposed generators, the differences from Hamming did not exceed 0.02 AUC, and no generator consistently achieved higher predictive discrimination. The results therefore do not support a general claim that

nonlinear generators improve prediction accuracy. Their principal contribution lies instead in the mathematical properties established in Section 4 and the ability to adjust the response to endpoint discrepancies.

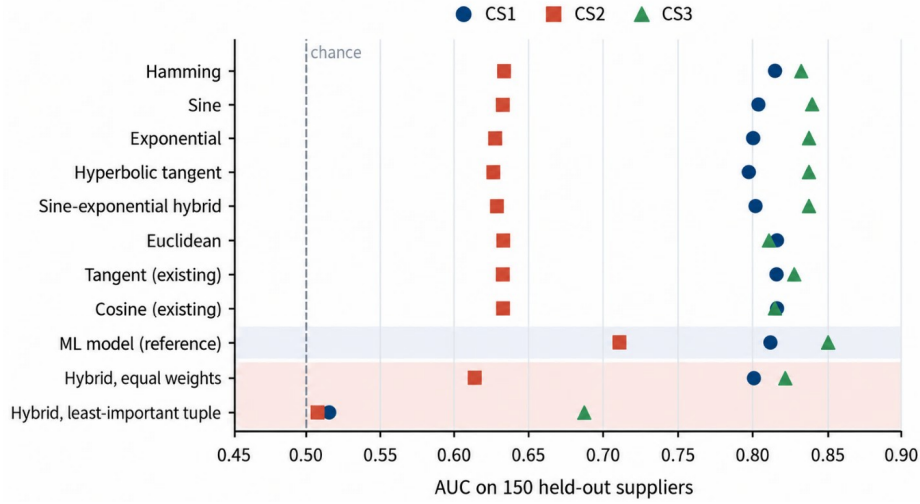


Figure 4. AUC comparison of the proposed similarity measures, reference measures and ablation configurations using 150 held-out suppliers per simulated case

Note: AUC = area under the receiver operating characteristic curve; CS = case study; ML = machine learning.

Two ablation experiments were conducted to identify the contributions of feature selection and criterion weighting. In the first, the hybrid similarity measure was evaluated using equal attribute weights. In the second, the selected sub-attributes were replaced with the least important sub-attributes identified by the predictive model.

Replacing the selected tuple with the least important features reduced the AUC to 0.516, 0.509 and 0.688 in CS1–CS3, respectively. The first two values were close to random discrimination. In contrast, replacing the XAI-derived weights with equal weights changed the AUC by no more than approximately 0.02.

These findings indicate that the choice of sub-attributes had a substantially greater influence on discrimination performance than their relative weighting in the simulated cases. The Shapley-based selection procedure was therefore the main empirical contributor to the performance of the resulting similarity scores.

The classifier achieved cross-validated AUC values of 0.792, 0.682, and 0.766 in CS1–CS3, respectively. The comparatively weaker discrimination in CS2 suggests that closely ranked supplier characteristics should be reviewed carefully before making a final decision.

The validation results indicate that the similarity-based decision model retained useful discriminatory information after reducing the original feature set from twelve to four selected sub-attributes.

Nevertheless, the held-out observations were generated from the same underlying process as the training data. The reported AUC values therefore provide evidence of internal validation under controlled conditions, rather than independent confirmation of the framework’s effectiveness in operational industrial procurement. Further evaluation using real supplier records would be necessary to establish its practical generalisability.

8 Robustness and Sensitivity Analysis

Industrial supplier rankings may be affected by modelling choices, estimated criterion weights and the uncertainty associated with different information sources. Sensitivity analysis was therefore conducted to examine whether the proposed recommendations remained consistent under variations in these factors.

Four sources of variation were examined using the hybrid generator as the reference measure: the generator parameter, criterion weights, pole weights, and removal of individual evaluation criteria.

8.1 Influence of the Generator Parameter

The rankings were recalculated for $\lambda \in \{0.25, 0.5, 1, 2, 3, 5, 8, 12\}$.

Increasing λ generally reduced the similarity scores and brought them closer together. Among the three parameterised generators, the hybrid formulation produced the most stable rankings over the examined parameter grid.

For CS1 and CS2, the hybrid generator preserved the complete supplier ordering across all tested values. In CS3, P4 remained the highest-ranked supplier throughout, although P1 and P2 exchanged positions when $\lambda \geq 3$, and P7 and P8 exchanged positions when $\lambda \geq 5$.

The exponential and hyperbolic-tangent generators showed greater sensitivity. In CS1, both followed the Hamming ordering, with B8 ahead of B6, when $\lambda \leq 1$. Their ordering reversed for parameter values between 2 and 3 and generally returned to the original order when $\lambda \geq 5$. In CS3, both generators placed P2 above P4 when $\lambda \geq 8$.

For large parameter values, the exponential and hyperbolic-tangent generators increasingly approach a step-like transformation in which nonzero discrepancies receive values close to one. Consequently, suppliers with several small deviations may receive similar penalties to those with larger deviations. The sine component moderates this behaviour in the hybrid generator.

Based on the examined simulations, values of λ between 1 and 3 provided a reasonable compromise between sensitivity and ranking stability. The hybrid generator was the most stable parameterised option within the tested settings, although this observation does not establish an optimal parameter range for all industrial decision problems.

The highest-ranked supplier remained unchanged across the proposed generators for the evaluated parameter values up to $\lambda = 5$.

8.2 Sensitivity to Attribute Weights

The XAI-derived criterion weights represent estimates of predictive importance and may vary with the training data. To examine their influence, 2,000 alternative weight vectors were generated from a Dirichlet distribution centred on the original weights, with a concentration parameter of 40.

The resulting coefficient of variation was approximately 15%–20% per weight. Each sampled vector was used to recalculate the supplier rankings.

In CS2, F6 and F4 retained the first and second positions in every simulation. CS1 showed greater sensitivity: B1 ranked first in 68% of the simulations, while B3 ranked first in 30%. Thus, the two leading suppliers were generally stable as a group, although their relative ordering was less certain. B7 remained last in 97% of the simulations.

In CS3, P4 retained first place in 95% of the simulations, while P1 and P2 frequently exchanged the second and third positions.

The results show that the stability of supplier rankings depends on the separation between competing alternatives. Small differences in similarity scores may lead to changes in rank when the criterion weights are perturbed, even when the overall group of preferred suppliers remains similar.

For intelligent procurement systems, such information provides a basis for distinguishing relatively stable recommendations from decisions that require further examination.

8.3 Sensitivity to Pole Weights

Pole weights determine the relative influence of organisational units, planning horizons or evidence sources in the *m*-Polar IVNHSS assessment.

To investigate this effect, supplier rankings were recalculated under equal pole weights and three additional scenarios in which one pole received a weight of 0.70 and the remaining two received 0.15 each.

The CS2 ranking remained unchanged across the examined scenarios. In CS1, B6 and B8 exchanged positions when either the Procurement Department or Sustainability Office received the dominant weight. In CS3, P1 and P2 exchanged positions only when the third-party audit received the greatest weight.

The highest-ranked supplier remained unchanged in all three cases.

These findings indicate that the relative importance assigned to information sources can influence closely ranked suppliers without necessarily altering the leading recommendation. They also illustrate the value of retaining separate pole assessments rather than immediately combining all available information into a single evaluation.

8.4 Sensitivity to Criterion Removal

The final analysis examined the effect of removing individual evaluation criteria. Each criterion was assigned a weight of zero in turn, and the remaining weights were renormalised before recalculating the rankings.

This intervention produced more substantial changes than moderate weight perturbations.

In CS1, removing the Labour-rights audit score criterion moved B8 from fourth to first place and B1 from first to fourth. The leading recommendation in this case therefore depended strongly on the inclusion of the social criterion. Removing Delivery reliability caused only B1 and B3 to exchange the two highest positions.

In CS2, removing Chemical compliance altered some lower-ranked positions, while the leading suppliers remained unchanged. In CS3, P4 ranked either first or second under every criterion-removal scenario.

These results indicate that ranking stability under moderate weight changes does not necessarily imply robustness to the removal of an influential criterion. For industrial supplier evaluation, this distinction is important because the exclusion of environmental, social or operational characteristics may substantially alter the preferred alternative.

Taken together, the sensitivity analyses show that the proposed framework provides more than a single supplier ranking. It allows decision makers to examine how the recommendations depend on mathematical parameters, data-derived weights, information sources and the inclusion of individual criteria.

The results also reinforce the importance of interpreting small differences in similarity scores cautiously. Stable rankings offer stronger support for a recommendation, whereas unstable rankings identify cases in which additional evidence or managerial review may be appropriate.

9 Discussion and Industrial Implications

The proposed framework integrates explainable machine learning with uncertainty-aware similarity measures to support intelligent supplier selection. The findings provide insights into the mathematical properties of supplier comparison methods, the contribution of data-driven feature selection, and the robustness of decisions made under uncertain information.

9.1 Mathematical Contribution and Decision Consistency

The principal theoretical contribution is the construction of a class of distance and similarity measures based on concave generator functions. Previous research has developed individual distance and similarity measures for neutrosophic and m -Polar interval-valued hypersoft structures [17–21]. The present study extends this work by identifying general conditions under which transformed endpoint discrepancies satisfy the metric axioms.

The proposed construction provides a common mathematical basis for selecting admissible generators rather than examining each functional form independently. The analysis also demonstrates that a particular convex tangent transformation fails to satisfy the triangle inequality when used in the proposed distance formulation.

These properties are relevant to industrial decision systems that involve repeated comparisons between uncertain supplier profiles. Although the proposed generators produced similar predictive discrimination in the simulated cases, their mathematical properties remain important when distance measures are used for clustering, comparison, or consensus analysis.

The sensitivity parameter provides additional flexibility by controlling how different deviations from an ideal supplier profile contribute to the distance. However, the experimental results do not establish that increasing sensitivity necessarily improves predictive accuracy or ranking stability.

9.2 Explainable Artificial Intelligence and Intelligent Supplier Evaluation

The most important empirical finding concerns the selection of evaluation sub-attributes. The ablation experiments showed that replacing Shapley-selected features with the least important features substantially reduced predictive discrimination, whereas assigning equal weights to the selected features had a comparatively small effect.

This suggests that selecting informative characteristics was more consequential than refining their weights under the examined simulation conditions. The finding highlights the role of data-driven feature selection in structuring intelligent supplier evaluation.

The integration of gradient boosting and Shapley attribution also provides explanations at two levels. Global attributions identify the characteristics retained for detailed assessment, while local explanations indicate which factors contribute positively or negatively to individual supplier predictions.

Nevertheless, Shapley values describe the behaviour of the fitted predictive model and should not be interpreted as causal effects. The derived criteria and weights therefore provide analytical support for procurement decisions rather than replacing organisational priorities or expert judgement.

9.3 Representation of Multiple Sources of Uncertainty

The m -Polar structure permits different assessment perspectives to be represented without immediately combining them into a single score. The three cases demonstrate its use for organisational departments, planning horizons, and evidence sources.

In CS1, the poles represented assessments from procurement, sustainability, and operations personnel. In CS2, interval widths reflected uncertainty associated with different planning horizons. In CS3, separate poles represented third-party audits, supplier self-assessments, and on-site inspections.

This flexibility is relevant to industrial procurement, where information may vary considerably across organisational functions and external sources. Interval-valued evaluations retain these differences during supplier comparison.

However, narrower intervals do not necessarily indicate more reliable information. The reciprocal-width weighting rule adopted in this study reflects an assumption about assessment precision, and its suitability depends on how the intervals are constructed. Source credibility and assessment uncertainty should therefore be examined separately when applying the framework.

9.4 Implications for Industrial Decision Support

The results have three implications for intelligent procurement systems.

First, predictive learning and uncertainty-aware ranking can perform complementary functions. Machine learning identifies informative supplier characteristics and screens candidates, while similarity measures support the subsequent comparison of retained suppliers under uncertain assessments.

Second, the framework provides interpretable information at different decision stages. Shapley attributions explain the predictive model, whereas similarity scores and sensitivity analyses help decision makers understand how criterion weights, information sources, and generator choices affect supplier rankings.

Third, ranking stability should be considered alongside similarity scores. Closely ranked suppliers may exchange positions when modelling assumptions change. A small numerical advantage should therefore not be treated as sufficient evidence for a definitive procurement decision.

These findings support the design of more transparent industrial decision-support procedures. Nevertheless, the present results demonstrate the framework's behaviour under controlled simulation conditions rather than its effectiveness in an operational procurement environment.

9.5 Limitations and Future Research

The main limitation is the reliance on simulated supplier records. Although the simulation allowed controlled evaluation of nonlinear relationships and uncertainty, the reported AUC values do not establish predictive performance in real industrial settings. Independent validation using actual supplier records remains necessary.

A second limitation concerns the use of predictive feature importance for sub-attribute selection and weighting. Shapley attributions may vary with feature correlations, model specification, and background data. The weaker predictive performance observed in CS2 illustrates the need for caution when interpreting closely ranked characteristics.

The selection of one sub-attribute per evaluation category also reduces the information retained by the decision model. Future studies could investigate procedures that allow several relevant sub-attributes to be included within each category.

In addition, exact enumeration of Shapley coalitions becomes computationally expensive as the feature dimension increases. Larger industrial datasets may require more scalable attribution methods.

Finally, the current framework assumes monotonic preference directions after transforming cost-type criteria. Target-type attributes, such as preferred delivery windows, require further methodological development. Future research should also examine source reliability, correlated evaluation attributes, and uncertainty in the estimated criterion weights.

10 Conclusions

This study developed an explainable AI-based intelligent decision framework for sustainable supplier selection under uncertainty. The framework integrated gradient-boosting prediction, Shapley-value attribution, and m -Polar interval-valued neutrosophic hypersoft evaluations to support data-driven feature selection and uncertainty-aware supplier ranking.

A class of concave generator functions was introduced to construct weighted distance and similarity measures satisfying defined mathematical properties. Four nonlinear generators were examined, and the theoretical analysis established conditions for metric consistency while identifying a triangle-inequality violation associated with a specific tangent transformation.

The framework was evaluated using three simulated industrial supplier selection cases involving electric-vehicle battery cells, organic-cotton fabric, and compostable packaging. The hybrid similarity measure achieved AUC values of 0.802, 0.630, and 0.837 on 150 held-out suppliers per case. Ablation experiments indicated that sub-attribute selection contributed more to predictive discrimination than criterion-weight adjustment. Sensitivity analysis further showed that the hybrid generator provided relatively stable rankings under the examined parameter settings, although some closely ranked suppliers remained sensitive to modelling choices.

The findings indicate that explainable machine learning and uncertainty-aware similarity measures can be combined to support transparent industrial supplier evaluation. The proposed framework provides a mathematical basis for interpretable ranking and allows decision makers to examine the stability of recommendations under different assumptions.

As the experiments were based on simulated data, further validation using real industrial procurement records is required before practical effectiveness can be established.

Author Contributions

Conceptualization, M.S. and J.M.M.; methodology, M.S.; software, M.S.; validation, M.S. and J.M.M.; formal analysis, M.S.; investigation, M.S.; resources, M.S.; data curation, M.S.; writing—original draft preparation, M.S.;

writing—review and editing, M.S. and J.M.M.; visualization, M.S.; supervision, J.M.M.; project administration, M.S.; funding acquisition, J.M.M. All authors have read and agreed to the published version of the manuscript.

Data Availability

The data used to support the research findings are available from the corresponding author upon request.

Conflicts of Interest

The authors declare no conflicts of interest.

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