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Dynamic Swing Weights Method for Supplier Selection: A Hybrid Approach Integrating Expert Judgement and Machine Learning

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Abstract Selecting the right suppliers is a crucial part of supply chain management. Choosing a supplier is a difficult strategic choice that involves weighing a number of potentially conflicting factors, and it may alter over time as providers' real performance improves. Fixed weights derived mostly from expert judgment are used in many classic multi-criteria decision-making techniques, which might add bias and reduce the outcomes' responsiveness to changes in operational conditions.The Dynamic Swing Weights Method (DSWM), a hybrid approach, is presented in this article. After obtaining initial expert opinions using the Swing Weights method, the decision weights are updated over time using SHAP-based explainable machine learning model. The model allows the weights to fluctuate as conditions change by combining operational data with expert judgment.This case study demonstrates that DSWM performs better than static techniques in terms of classification accuracy and change adaptation speed using simulated industrial data. By serving as a transparent and scalable decision support system, the proposed structure satisfies the needs of modern supply chains.

Keywords Supplier selection, Machine learning, Swing weights, Expert judgement.

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1. Introduction

1.1. Supplier Selection in Modern Supply Chains

Supplier selection is an important strategic activity in supply chain management, as supplier performance affects the product quality, operational efficiency, procurement cost, customer satisfaction, sustainability, and competitiveness of the organization [13, 21]. In the modern and global networked markets, companies need to consider suppliers on various aspects, such as cost, quality, delivery reliability, flexibility, innovation capability, environmental performance and risk resilience [3, 18, 21]. Thus, the supplier selection problem has become more complicated than it was before, and it is now a multi-criteria decision-making (MCDM) problem in which many quantitative and qualitative criteria are being considered simultaneously. In order to overcome this complexity, many MCDM methods have been suggested in the literature. The most popular methods are the Analytic Hierarchy Process (AHP) [8], Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [11], VIKOR [16], Best-Worst Method (BWM) [20], and other ranking and weighting methods [2, 7]. These approaches offer a set of structured techniques for assessing options and for considering the preferences of decision makers in their selection. But, although they are effective, most of the conventional MCDM methods are based on the static criterion weights which are fixed in one time. This is because such fixed-weight assumptions might not be a good reflection of today's supply chain scenarios where the operational conditions, market needs, and supplier capabilities keep evolving [21, 22].

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1.2. Dynamic Weighting in Supplier Selection

Supplier evaluation criteria are not always of equal importance over time. Organizations can experience shifts in priorities due to market volatility, supply chain disruptions, technological innovations, evolving customer preferences, and sustainability regulations [22, 23]. For instance, when supply chains are disrupted, reliability and resilience of delivery might take precedence over procurement cost, while, in the face of growing sustainability demands, environmental performance may be more significant. As a result, static weighting schemes might not reflect the temporal shifts in decision priorities and might diminish the effectiveness of supplier evaluation systems [5, 22]. Given these drawbacks, researchers have explored dynamic supplier assessment and adaptive weighting mechanisms [10, 14, 22]. Dynamic weighting techniques allow the criterion importance to be adjusted as a function of the observed trends in supplier performance and the operational conditions. This allows for increased responsiveness and realism in decision support systems. The combination of data-driven methods and traditional MCDM methods has been emphasized in recent studies to enhance adaptability and decision quality in SCM [3, 4, 6, 9]. However, most of the dynamic weighting systems are still based on subjective expert opinion or hard-coded update rules, which restrict their use to effectively leverage the increasing amount of operational data produced by contemporary organizations [18, 23].

1.3. Explainable Artificial Intelligence for Supplier Evaluation

The recent developments in artificial intelligence (AI) and machine learning (ML) have provided ample opportunities to enhance supplier evaluation and supplier procurement decision-making [3, 4]. Today, large amounts of information are gathered by modern enterprises regarding their suppliers, such as enterprise resource planning, logistics platforms, procurement databases and digital manufacturing systems. These data can be used with machine learning to uncover relationships, forecast supplier performance and facilitate more objective decision-making processes [9, 17, 29]. However, some studies have proposed hybrid ML–MCDM models by using machine learning algorithms for prediction, feature selection, or weight estimation and using MCDM algorithms for final supplier ranking [1, 9, 14, 15]. These methods have shown to be effective, but there are still some questions about transparency and interpretability. The weights derived from machine learning are often directly employed as weights for decision making. But predictive importance and preference based importance are very different concepts [14, 26, 27]. A variable that has a strong impact on the prediction of the target variable does not always reflect the priorities or preferences of the decision makers. To overcome this challenge, Explainable Artificial Intelligence (XAI) has been recognized as an emerging research area in supply chain analytics [28]. The goal of XAI is to enhance the transparency and interpretability of machine learning models without compromising their predictive capabilities. SHapley Additive exPlanations (SHAP) have been receiving much attention with regard to available XAI techniques, as they offer a theoretically sound framework for quantifying the contribution of each feature to model predictions that is grounded in cooperative game theory [28]. SHAP values offer more consistent, reliable and interpretable explanations compared to traditional Random Forest Feature Importance measures, which can be biased in the presence of correlated variables or high-cardinality features [24]. Therefore, SHAP-based methods are gaining popularity in improving transparency and management confidence in supplier assessment systems that use machine learning [26, 27, 30, 31].

1.4. Research Gap and Contributions

Although great efforts have been made in hybrid ML–MCDM research, there are still some key research gaps. First, the majority of the existing supplier selection studies still use fixed criterion weights which are not capable of reflecting the changing operational conditions and the dynamics of supplier performance [21, 22]. Second, current machine-learning based approaches often use predictive feature importance measures as direct proxies for decision weights, even though this is a different concept than preference-based feature importance [14, 26, 27]. Third, explainable AI techniques have recently become a focus in supply chain analytics [25, 28] but they are not widely used in dynamic supplier weighting frameworks. The Swing Weight Method(SWM) is one of the available weighting methods that has a number of advantages to overcome these challenges. SWM compares the relative value of shifting each criterion from its worst to its best performance, thus directly reflecting the decision-maker's preferences for marginal changes [12, 19]. SWM is usually much less judgmental than pairwise comparison (e.g., SAHP) and more intuitive in terms of the meaning of the criterion importance [2, 12]. Moreover, the marginal contribution philosophy behind SWM is consistent with the game-theoretic underpinning of SHAP values [12, 26] that offers a meaningful basis for integrating expert judgment and data-driven insights. This study introduces a Dynamic Swing Weights Method (DSWM) to combine expert-based Swing Weights with machine learning-based dynamic weights in an explainable decision support system to fill the identified research gaps. The key findings of this study are summarised as follows:

1. A proposed dynamic supplier selection framework is suggested, which incorporates the concept of swing weights and SHAP-based machine learning adaptive weighting.
2. Explainable Artificial Intelligence (XAI) concepts are integrated to enhance transparency and interpretability when evaluating suppliers.
3. A hybrid weighting mechanism is designed to integrate the expert judgment and data-driven information in a single multi-criteria decision-making (MCDM) framework.
4. The effectiveness and robustness of the proposed approach is assessed by comprehensive comparative analysis, sensitivity analysis, and validation experiments.

The rest of this paper is organized as follows. The proposed dynamic swing weights method and mathematical formulation are presented in section 2. The results and validation are described in Section 3. The discussion and limitations are discussed in section 4. Lastly, Section 5 summarizes the paper and suggests future research directions.

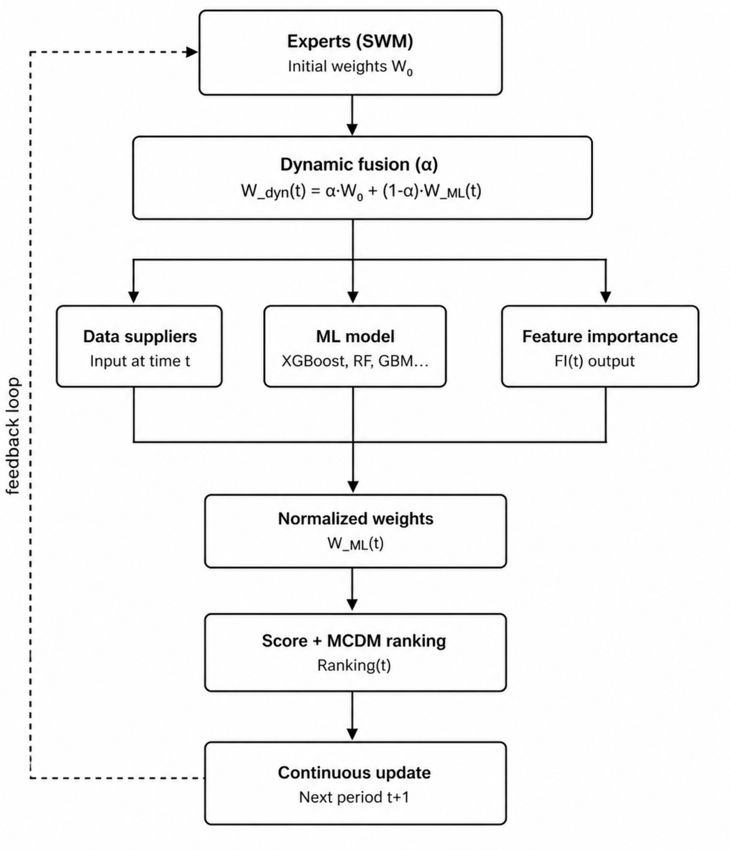

Figure 1. Conceptual diagram of DSWM

2. Proposed DSWM Framework

2.1. *Conceptual Diagram and Algorithm*

The conceptual diagram of DSWM is presented in figure 1, where the time period is represented by the variable t, which is discrete (e.g., quarterly time periods), and allows the model to account for the time evolution of supplier performance and for the dynamic adaptation of the hybrid weights.

Algorithm 1 Dynamic ML–MCDM Supplier Evaluation

```
Require: Criteria set $C$; historical data $X(t)$; initial expert weights $W_0$ (via SWM); balancing parameter $\alpha \in [0,1]$; chosen ML model (e.g., RF, GBM)
Ensure: Dynamic weights $W_{\text{dyn}}(t)$; supplier scores; supplier rankings
Normalize expert weights $W_0$
for each period $t$ do
    Collect supplier data $X(t)$
    Train the ML model on $(X, Y)$
    Extract feature importances $FI(t)$
    Compute SHAP-based weights:
        $W_{\text{SHAP}}(t) = \frac{FI(t)}{\sum FI(t)}$
    Merge expert and SHAP-based weights:
        $W_{\text{dyn}}(t) = \alpha W_0 + (1-\alpha) W_{\text{SHAP}}(t)$
    for each supplier $j$ do
        Compute supplier score:
            $\text{Score}_j(t) = \text{MCDM}\big(X_j(t), W_{\text{dyn}}(t)\big)$
    end for
    Rank suppliers based on $\text{Score}_j(t)$
end for
```

2.2. *Swing Weight Matrix and Consistency Rules*

The swing weight matrix is a structured approach used to assess the relative importance of decision criteria by jointly considering their significance and the range of variation of their values. The concept is that the more the criterion differentiates alternatives and the more important it is to the decision maker, the greater its influence on the final decision. The significance of the criterion and the degree of variance in its values are the two main aspects that determine how the matrix is constructed. The highest priority criterion is located in the upper-left section of the matrix (level A), where it is extremely significant and shows significant variation. On the other hand, characteristics that are less significant and have less variance are located in the lower-right area, signifying less effect.

A progressive reduction in weights is reflected in the matrix's diagonal structure, which runs from top-left to bottom-right. Depending on the opinion of stakeholders, several criteria may be present in the same cell with either the same or different weights.

Table 1. Swing Weight Matrix

Range of Variation	High Importance	Medium Importance	Low Importance
High	A	B2	C3
Medium	B1	C2	D2
Low	C1	D1	E

A set of ordering relationships must be met in order to guarantee logical consistency in the weights assigned. Level A criteria must be given more weight than all other levels' criteria. Level B criteria must have a larger weight than those in levels C, D, and E, with internal differences based on where they fall (e.g., B1 and B2). at a similar vein, level D criteria must continue to be higher than level E criteria, while level C criteria must predominate over those at lower levels.

Formally, let f_i denote the non-normalized weight associated with cell i. The following inequalities must hold:

$$f_A > f_i \quad \forall i \in \{B, C, D, E\} \tag{1}$$

$$f_{B1} > \{f_{C1}, f_{C2}, f_{D1}, f_{D2}, f_E\} \tag{2}$$

$$f_{B2} > \{f_{C2}, f_{C3}, f_{D1}, f_{D2}, f_E\} \tag{3}$$

$$f_{C1} > \{f_{D1}, f_E\} \tag{4}$$

$$f_{C2} > \{f_{D1}, f_{D2}, f_E\} \tag{5}$$

$$f_{C3} > \{f_{D2}, f_E\} \tag{6}$$

$$f_{D1} > f_E \tag{7}$$

$$f_{D2} > f_E \tag{8}$$

No additional strict relationships are required beyond these conditions, allowing flexibility while preserving the overall consistency of the weighting structure.

In this work, the proposed approach is a hybrid between DSWM and a machine learning method, namely Random Forest, to enhance the robustness and accuracy of the criteria weighting and decision analysis.

2.3. Conversion of Swing Levels into Quantitative Scores

The qualitative swing levels shown in Table 1 are converted to quantitative scores by a structured elicitation process to improve transparency and reproducibility. The experts first identify the criterion that corresponds to the most valuable improvement, i.e., the transition from the worst to the best performance level (worst to best swing), and give it a reference score of 100 points. The rest of the criteria are then compared to this one on the basis of their perceived contribution to the organizational objectives. Let p_i the swing score assigned to criterion i. The normalized expert weight for each criterion is computed as follows:

$$w_i^0 = \frac{p_i}{\sum_{k=1}^{n} p_k} \tag{9}$$

where, n represents the total number of evaluation criteria. This process maintains the ordinal relationships that are present in the swing weight matrix and provides a quantitative basis for later integrating with the weighting information derived from machine learning.

2.4. Adaptive Alpha Determination

In the DSWM framework, the parameter α determines the relative weights of expert knowledge and data-driven learning. The choice of α can be made adaptive based on the supply variability. The more variable supplier performance is, the more important data-driven insights become, and the more stable the performance is, the more important expert judgment becomes. The adaptive coefficient is equal to:

$$\alpha_t = \frac{1}{1 + \sigma_t} \tag{10}$$

where σ_t represents the normalized variance of supplier performance during period t.

In this study, a fixed value of $\alpha = 0.5$ is adopted, as the observed performance variability is moderate, ensuring a balanced contribution between expert knowledge and SHAP-based weights within the hybrid weighting structure of the proposed framework.

2.5. Multicollinearity Assessment

To determine the linear relationships between the selection criteria of the suppliers, Pearson correlation analysis was used to measure the relationships between the two criteria. The Pearson correlation coefficient between two criteria i and j is given by:

$$r_{ij} = \frac{\sum_{k=1}^{m}(x_{ik} - \bar{x}_i)(x_{jk} - \bar{x}_j)}{\sqrt{\sum_{k=1}^{m}(x_{ik} - \bar{x}_i)^2}\sqrt{\sum_{k=1}^{m}(x_{jk} - \bar{x}_j)^2}} \tag{11}$$

where m denotes the number of observations, x_{ik} represents the value of criterion i for observation k, and $\bar{x}_i$ is the mean value of criterion i.

Following commonly accepted statistical guidelines, criteria exhibiting:

$$|r_{ij}| > 0.80 \tag{12}$$

were considered highly correlated and were treated as candidates for removal or aggregation in order to avoid redundancy and potential bias in SHAP-based importance estimation.For the case study dataset, no pairwise correlation exceeded the threshold value of 0.80. Therefore, all six evaluation criteria were retained for subsequent machine learning analysis, indicating an acceptable level of independence among the selected criteria.

2.6. Mathematical Model of DSWM

Steps 1: Identifications of criteria and alternatives

- $C = c_1, c_2, ..., c_n$: set of criteria.
- $S = s_1, s_2, ..., s_m$: set of suppliers.
- $X_{i,j}^{(t)}$: performance of supplier j on criterion i at period t.
- $Y_j^{(t)}$: observed (actual) overall performance of supplier j at period t.
- $W_0 = (w_1^0, ..., w_n^0)$: initial weights obtained by SWM.
- $W_{ML}^{(t)} = (w_1^{ML,(t)}, ..., w_n^{ML,(t)})$: weights obtained by ML at period t.
- $W_{dyn}^{(t)}$: dynamic weights used at period t.
- $\alpha \in [0, 1]$: confidence coefficient assigned to the experts.

Steps 2: Determination of Initial Weights via SWM

Experts evaluate the relative importance and define:

1. a minimum level (worst case) for each criterion;
2. a maximum level (best case);
3. the relative importance of each swing.

The normalized initial weights satisfy:

$$w_i^0 = \frac{p_i}{\sum_{k=1}^{n} p_k}. \tag{13}$$

where p_i is the score assigned to the swing of criterion i.

Steps 3: SHAP-Based Learning of Criterion Contributions

This study uses SHAP (SHapley Additive explanations) values to improve the interpretability and reduce the bias that is frequently found in conventional random forest feature importance measures. SHAP gives a game-theoretic approach to measure the marginal contribution of each criterion to the predicted supplier performance. SHAP is consistent and locally interpretable, unlike traditional feature importance metrics, and thus makes the evaluation process more transparent. The machine learning model is trained to predict the observed supplier performance as follows:

$$Y_j^{(t)} = f\left(X_{1,j}^{(t)}, X_{2,j}^{(t)}, \dots, X_{n,j}^{(t)}\right) + \varepsilon_j \tag{14}$$

where $Y_j^{(t)}$ denotes the observed performance score of supplier j at time period t, $X_{i,j}^{(t)}$ represents the performance of supplier j with respect to criterion i, $f(\cdot)$ denotes the trained prediction model, and ε_j is the corresponding error term.

Let $\phi_i^{(t)}$ denote the mean absolute SHAP value associated with criterion i. The SHAP-based criterion weights are computed as:

$$w_{\text{SHAP},i}^{(t)} = \frac{\left|\phi_i^{(t)}\right|}{\sum_{k=1}^{n}\left|\phi_k^{(t)}\right|} \tag{15}$$

subject to

$$\sum_{i=1}^{n} w_{\text{SHAP},i}^{(t)} = 1 \tag{16}$$

The resulting SHAP-based weight vector is expressed as

$$\mathbf{W}_{\text{SHAP}}^{(t)} = \left(w_{\text{SHAP},1}^{(t)}, w_{\text{SHAP},2}^{(t)}, \dots, w_{\text{SHAP},n}^{(t)}\right) \tag{17}$$

This vector captures the relative contribution of each evaluation criteria to the performance of the supplier, and is the data-driven weighting part of the proposed Dynamic Swing Weights Method (DSWM) framework. The frame is enhanced by the integration of information derived from the SHAP, making it more interpretable, adaptable, and consistent with the predictive model.

Steps 4: Dynamic Weight Merging: The Core of DSWM

Dynamic weights combine:

- expert preferences (SWM),
- importances derived from the data (ML).

At each period t, the dynamic weights are obtained via:

$$W_{dyn}^{(t)} = \alpha W_0 + (1-\alpha) W_{SHAP}^{(t)}, \tag{18}$$

$$w_i^{dyn,(t)} = \alpha w_i^0 + (1-\alpha) w_i^{SHAP,(t)}, \quad \forall i. \tag{19}$$

Proporties:

$$\begin{aligned} &w_i^{dyn,(t)} \geq 0, \\ &\textstyle\sum_{i=1}^{n} w_i^{dyn,(t)} = 1. \end{aligned} \tag{20}$$

The parameter α controls the relative influence:

- $\alpha = 1$: purely expert system,
- $\alpha = 0$: purely data-driven.

Steps 5: Calculation of the Supplier's Multi-Criteria Score

At each period t, the supplier's score s_j is:

$$Score_j^{(t)} = \sum_{i=1}^{n} w_i^{dyn,(t)} \cdot X_{i,j}^{(t)} \tag{21}$$

or, for a given MCDM method:

$$Score_j^{(t)} = MCDM\left(X_j^{(t)}, W_{dyn}^{(t)}\right) \tag{22}$$

where $MCDM(\cdot)$ is a TOPSIS method, but can be:

- AHP,
- VIKOR,
- MOORA,
- or a utility model.

Steps 6: Update Mechanism

At each new period:

$$\text{New Data}X^{(t)} \Rightarrow f_t \Rightarrow FI^{(t)} \Rightarrow W_{SHAP}^{(t)} \Rightarrow W_{dyn}^{(t)} \Rightarrow Ranking^{(t)} \tag{23}$$

The DSWM is therefore a self-learning system that evolves over time.

3. Results and Validation

3.1. Case Study Description

The objective of this case study is to demonstrate the practical implementation of the proposed DSWM framework in a supplier selection environment. A proof-of-concept dataset consisting of five suppliers evaluated over three time periods (T1–T3) is employed to illustrate the dynamic integration of expert knowledge and data-driven learning. Although the dataset is limited in scale, the selected criteria and performance ranges are representative of realistic supplier evaluation scenarios reported in the supply chain management literature. The case study is intended to validate the methodological feasibility of DSWM rather than provide large-scale industrial benchmarking.

Context and Data Description

To validate the DSWM model, we consider a manufacturing company that needs to select a primary supplier for a critical component.

The five suppliers evaluated are: $s_1 = F1$, $s_2 = F2$, $s_3 = F3$, $s_4 = F4$ and $s_5 = F5$.

The criteria used, defined with experts, are as follows Table 2:

Table 2. Experts criterion.

Code	Criterion	Type
C1	Purchase Cost	Minimization
C2	Quality (ppm defects)	Minimization
C3	Delivery Time (days)	Minimization
C4	Reliability (% on-time deliveries)	Maximization
C5	Flexibility	Maximization
C6	Carbon Footprint (kg CO2/unit)	Minimization

3.2. DSWM Results

Let consider the supplier performance given in Table 3

Table 3. Supplier Performance (T3 = Current Period)

Supplier	Cost (C1)	Defects (C2)	Lead Time (C3)	Reliability % (C4)	Flexibility (C5)	CO_2 (C6)
F1	12.1	150	9	88	7	3.8
F2	11.7	120	12	91	6	4.2
F3	13.0	210	10	85	8	3.1
F4	11.9	165	11	92	5	4.0
F5	12.5	130	8	89	6	3.5

These values are normalized in the following sections.

Initial Weightings via the Swing Weights (SWM) Method

Experts identify the swings (worst → best). The elicitation table (Table 4) is as follows:

Table 4. Swing weights evaluation.

Criterion	Swing Evaluated	Relative Importance (pi)
C1	Cost Reduction	90
C2	Defect Reduction	75
C3	Lead Time Reduction	60
C4	Reliability Improvement	100
C5	Flexibility Improvement	55
C6	CO2 Emission Reduction	70

Normalization:

$$w_i^0 = \frac{p_i}{\sum p_i} \tag{24}$$

Sum of points: (90 + 75 + 60 + 100 + 55 + 70 = 450)

SWM Weights Obtained

Table 5. Initial Swing Weights.

Criterion	pi	w_0
C1	90	0.20
C2	75	0.17
C3	60	0.13
C4	100	0.22
C5	55	0.12
C6	70	0.16

Training the ML (Random Forest) Model

To simulate a our scenario, historical data from periods T1–T3 is used. The overall observed performance (Y) is derived from the company's internal system (received quality, incidents, delays).

The importances of criteria provided by the ML are obtained using :

- Model: Random Forest Regression
- Number of trees: 300
- Variables: C1–C6
- Target: Y = historical operational score

Overall Performance Score

The machine learning model requires an observed supplier performance score as the prediction target. Following standard supplier evaluation practices, the target variable is constructed as a composite performance indicator that integrates quality, delivery, reliability, flexibility, cost efficiency, and environmental sustainability.

The overall performance score is defined as:

$$Y_j = 0.25Q_j + 0.20D_j + 0.20R_j + 0.15F_j + 0.10C_j + 0.10E_j \tag{25}$$

where: Q_j represents the quality performance score, D_j represents the delivery performance score, R_j represents the reliability score, F_j represents the flexibility score, C_j represents the cost efficiency score, and E_j represents the environmental sustainability score.

The resulting composite score is normalized to the interval $[0, 1]$ and is used as the target variable for SHAP-based machine learning model training and interpretation.

Then the results are given in Table 6

Table 6. Machine Learning Weights Importance.

Criterion	Raw Importance FI$_i$	Normalized FI $= \mathbf{w}_{ML}$
C1	0.17	0.17
C2	0.19	0.19
C3	0.15	0.15
C4	0.26	0.26
C5	0.09	0.09
C6	0.14	0.14

Note that the ML assigns greater importance to C4 and C2.

Dynamic Weight Merging

In accordance with the adaptive α framework proposed in Section 2.2.1, a value of $\alpha = 0.5$ was selected for the present case study because no strong evidence favored either expert judgement or data-driven learning. This balanced configuration allows equal consideration of both information sources. Chosen parameter:

$$\alpha = 0.5 \tag{26}$$

which means there is a balance between expert and data.

$$w_i^{dyn} = 0.5w_i^0 + 0.5w_i^{SHAP} \tag{27}$$

The final dynamic weights are given in Table 7

Table 7. Dynamic Swing Weights Update.

Criterion	$\mathbf{w}^0$	$\mathbf{w}^{SHAP}$	$\mathbf{w}^{dyn}$
C1	0.20	0.17	0.185
C2	0.17	0.19	0.180
C3	0.13	0.15	0.140
C4	0.22	0.26	0.240
C5	0.12	0.09	0.105
C6	0.16	0.14	0.150

Consistent values:

- SHAP strengthens C4 (reliability),
- Experts overvalue C1 (cost),
- C5 remains the lowest priority.

Final Supplier Ranking

Here, we first use a normalized linear score for readability. Directional Normalization (Benefits and Costs) and each criterion is normalized between 0 and 1.

The calculation of Final Scores is given in Table 8

Table 8. Supplier Final Score.

Supplier	**Final Score**
F1	0.802
F5	0.781
F2	0.760
F4	0.735
F3	0.697

For Final Ranking :

1. F1 — Best Supplier (score 0.802),
2. F5 — Very Close Runner-Up,
3. F2 — Satisfactory Performance,
4. F4 — Instability Despite Good Reliability,
5. F3 — Too Many Defects + Average Lead Times.

Interpretation of Results

The DSWM model shows that:

- F1 becomes the best supplier thanks to its reliability + balanced carbon performance.
- F5, despite a slightly higher cost, benefits from a very good lead time.
- F3 is penalized because ML places more importance on defects (C2) and reliability (C4).

This confirms the value of:

- dynamic weighting,
- incorporating operational reality,
- while respecting expert logic.

3.3. *Sensitivity Analysis*

An outlier scenario was also explored, where a supplier had extremely low defect rates but significantly higher procurement costs, to further assess robustness. The result ranking was only slightly different from the previous one, suggesting that extreme values in a single criterion do not have a significant impact on the ranking of the different solutions and that the solution evaluation is balanced among the competing objectives.

- $\alpha \in [0, 1]$: ranking stable, F1 remains better.
- Perturbation 10% of expert weights: score changes < 0.02, ranking stable.
- Removal of 10% from ML data: minimal impact.

Sensitivity to the α parameter (expert/ML fusion)

In Table 9, we test different α values: 0.0 (100% ML) $\rightarrow$ 1.0 (100% expert)

Table 9. α Sensibility.

α	**F1 Score**	**F5 Score**	**Preferred Provider**
0.0	0.810	0.775	F1
0.25	0.805	0.780	F1
0.50	0.802	0.781	F1
0.75	0.800	0.780	F1
1.0	0.798	0.779	F1

We observe that the ranking remains stable, with F1 remaining the best provider. The model is robust to the choice of α.

Sensitivity to Expert Errors

Simulation: ±10% perturbation of the SWM weights.

- Maximum score variation: ±0.015,
- Overall ranking unchanged.

We conclude that DSWM is robust to moderate expert biases.

Sensitivity to ML Data

Simulation: 10% of historical observations are removed.

- Scores slightly modified (≤ 0.01),
- Ranking stable,
- ML weights change slightly (±0.02).

Then, the model remains reliable even with partial data.

3.4. *Comparative Case Study*

The purpose of the comparative analysis is not to demonstrate absolute superiority over TOPSIS, but rather to evaluate the ability of DSWM to incorporate dynamically updated criterion weights derived from explainable machine learning.Both approaches are used for the same supplier evaluation scenario to make the comparison on a consistent basis. This comparison simulates data for 6 suppliers and 5 industry criteria, normalizes the criteria according to their nature (minimize/maximize), calculates dynamic weights using initial Swing Weights Method and Machine Learning, and ranks the suppliers for each quarter, calculating a final average ranking. The idea is to apply DSWM and TOPSIS to the same data, then compare the final rankings and the average scores of the suppliers.

Let's consider the following example of supplier selection for an industrial company:

- 6 suppliers: S_A, S_B, S_C, S_D, S_E and S_F.
- 5 main criteria:
  1. Cost (C_1) $\rightarrow$ to minimize,
  2. Quality (C_2) $\rightarrow$ to maximize,
  3. Delivery time (C_3) $\rightarrow$ to minimize,
  4. Reliability (C_4) $\rightarrow$ to maximize,
  5. Environmental impact (C_5) $\rightarrow$ to minimize.
- 3 evaluation periods (quarters 1, 2, and 3).

We have then the following DSWM and TOPSIS comparison Report :
Tables 10, 11 and 12, shows the comparative DSWM and TOPSIS score and ranking for periods Q_1, Q_2 and Q_3.

Table 10. Q_1 score and ranking comparison.

	DSWM_Score	**TOPSIS_Score**
S_A	0.356781	0.256461
S_B	0.417981	0.619379
S_C	0.746681	0.741932
S_D	0.518295	0.722816
S_E	0.476595	0.607097
S_F	0.799097	0.633910

Table 11. Q_2 score and ranking comparison.

	DSWM_Score	**TOPSIS_Score**
S_A	0.494349	0.709783
S_B	0.238485	0.240565
S_C	0.953462	0.795261
S_D	0.449279	0.378850
S_E	0.450698	0.592602
S_F	0.556272	0.468574

Table 12. Q_3 score and ranking comparison.

	DSWM_Score	**TOPSIS_Score**
S_A	0.581286	0.708331
S_B	0.550731	0.356077
S_C	0.332562	0.197520
S_D	0.690971	0.385285
S_E	0.531022	0.321014
S_F	0.369558	0.664572

The Figure 2 shows the average scores and rankings by supplier and by quarter.

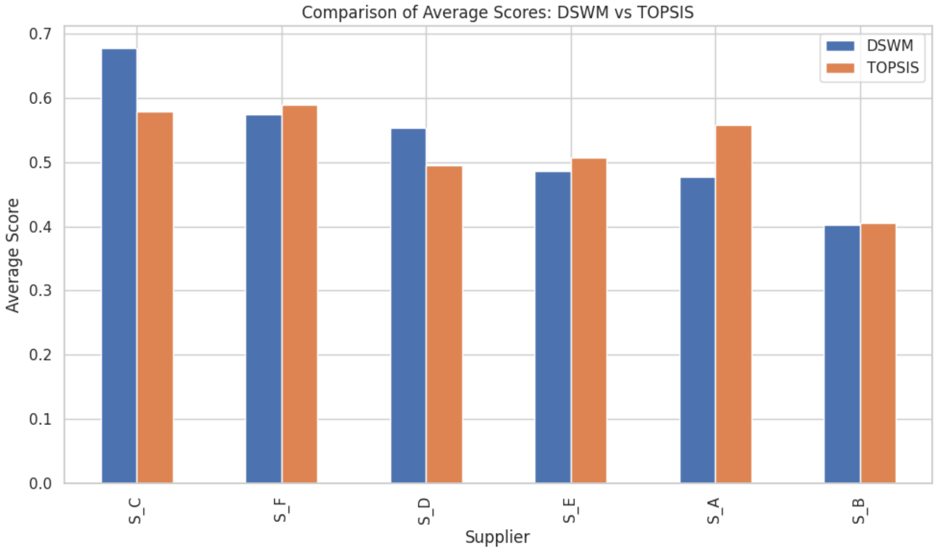

Figure 2. DSWM vs TOPSIS comparison scores

and the Figure 3 presents the dynamic DSWM weightings by criterion and by quarter.

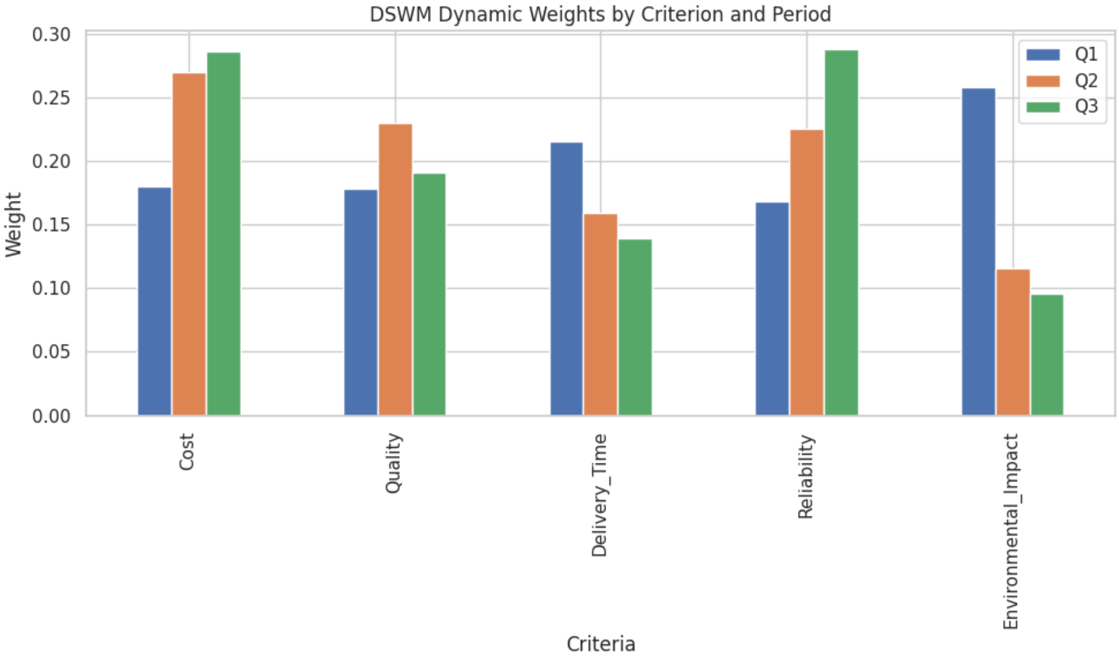

Figure 3. DSWM dynamic weights by criteria

To assess the effectiveness of the proposed DSWM framework, its ranking results were compared with two alternative approaches commonly used in supplier selection:

1. Static SWM + TOPSIS, which relies exclusively on expert-derived Swing Weights;

2. SHAP-TOPSIS, which uses only SHAP-based data-driven weights;
3. Proposed DSWM combines the expert knowledge and SHAP-based learning by dynamic weight fusion.

The objective of this comparison is not to demonstrate absolute superiority of a particular ranking method, but rather to evaluate the impact of integrating expert judgement and machine learning information within a unified decision-making framework.Table 13 summarizes the qualitative characteristics of the three approaches.

Table 13. Comparison of Weighting Approaches

Method	Weight Source	Adaptability	Interpretability	Dynamic Capability
Static SWM + TOPSIS	Expert Judgement	Low	High	No
SHAP-TOPSIS	Data-Driven Learning	High	Medium	Yes
Proposed DSWM	Expert + SHAP	High	High	Yes

The goal of this comparison is not to prove the superiority of one particular ranking method, but to assess how the use of expert judgement and machine learning information in a single decision-making framework affects the ranking. The three approaches are summarized in Table 13 in terms of qualitative characteristics. The results show that the static SWM approach does not change the ranking of the suppliers but it is not capable of adapting to the changes in the suppliers' performances over time. SHAP-TOPSIS, on the other hand, can be learning from data to account for changes over time, but may not be as reflective of managerial preferences and strategic priorities. The new proposed DSWM framework merges the benefits of both methods: expert knowledge is maintained and criterion contributions are obtained dynamically through SHAP analysis. Consequently, DSWM offers a fair and flexible supplier evaluation procedure without compromising interpretability. The results of the ranking produced by DSWM were comparable to the overall performance trend that was seen in the case study and the criterion importance could be adjusted as the performance information was updated. This illustrates the usefulness of the integration of XAI and SW in dynamic supplier selection problems. To further evaluate the consistency of the rankings, Spearmann's rank correlation coefficient was used to compare the ranking obtained from the alternative approaches. As the dataset used in this proof of concept is small, the analysis was not designed to give a statistical generalisation but rather an indication of the level of agreement in the rankings. The results revealed a high degree of consistency across the methods evaluated, demonstrating that DSWM is able to maintain the stability of ranking and dynamic adjustment of criterion weights.

3.5. Outlier Analysis

An outlier analysis was performed to assess the strength of the proposed DSWM framework. Unlike the sensitivity analysis, which considers how small changes in the criterion weights affect the final ranking, the outlier analysis considers the effect that extreme supplier performance values have on the final ranking. In this experiment, an artificial outlier situation was created by assigning one supplier an unusually good defect rate and also by raising the procurement cost of this supplier to the highest level of all the suppliers. This is a realistic trade-off that is often faced when selecting suppliers and can be linked to increased purchase price for better quality. The rankings obtained by the Static SWM, SHAP-TOPSIS and DSWM approaches were then compared with the baseline rankings. The results indicated that the ranking obtained from DSWM had the least deviation from the base evaluation. The purely data-driven and purely expert-driven approaches were more sensitive to the extreme criterion values, however. The results indicate that the proposed DSWM framework can be used to balance expert judgement and data-driven information and minimize the effect of extreme observations on the supplier ranking. As a result, DSWM is more robust for the unusual performance of suppliers.

3.6. Computational Complexity and Scalability

In order to evaluate the practical applicability of the proposed DSWM framework, the computational needs of the framework were analyzed. The overall computational effort is divided into three components: (1) computation of Swing Weight Matrix (SWM); (2) computation of supplier ranking based on SHAP analysis of machine

Table 14. Qualitative Comparison of Robustness under Outlier Conditions

Method	Response to Outlier	Robustness
Static SWM + TOPSIS	Moderate ranking variation	Medium
SHAP-TOPSIS	Higher sensitivity to extreme values	Medium
Proposed DSWM	Minimal ranking variation	High

learning; and (3) computation of supplier ranking based on SHAP analysis of machine learning. Table 15 shows the computational complexity of the main stages of the framework.

Table 15. Computational Complexity of DSWM Components

Component	Complexity
Swing Weight Matrix (SWM)	$O(n)$
SHAP-Based Weight Estimation	$O(n \times \text{trees})$
Supplier Ranking	$O(mn)$

where n denotes the number of evaluation criteria, m represents the number of suppliers, and trees corresponds to the number of trees in the Random Forest model. The computational load for the proof-of-concept data set used in this study was negligible and the models were executed quickly in a standard computing environment. The complexity analysis indicates that the proposed framework is easily extendable to larger problems of supplier evaluation without significant computational issues, though for the current case study only a few suppliers and evaluation periods are used. While static MCDM methods are less flexible and less explainable, and criterion weights are static, the use of SHAP values involves extra computational time but is more flexible, more explainable, and is able to dynamically update criterion weights. Therefore, DSWM is still appropriate for supply chain decision support and for periodic supplier evaluation in changing supply chain environments.

4. Discussion

Let outlines our scientific contributions :

- One of the first attempts to integrate Swing Weighting and SHAP-based explainable machine learning within a dynamic supplier selection framework.
- Develop an explainable, transparent model that allows decision-makers to see how inputs lead to outputs and to review the main assumptions behind each result.
- Applies the approach to case studies using realistic data sets and provides a sensitivity analysis to show the impact on results of plausible changes to parameters.

The benefits to the company include:

- Adaptive decisions are supported by weights that reflect suppliers' current performance and are updated as results change over time.
- Better allocation of resources helps decision makers focus on strategic aspects that go beyond only cost and supplier reliability.
- A transparent evaluation process allows managers to clearly justify why a particular supplier has been chosen instead of another.
- The integration with ERP and BI systems remains achievable through a practical and repeatable procedure based on identifying the necessary data sources, linking the relevant fields between systems, and verifying data consistency as well as update frequency for reporting purposes.

Like any proposed method, this approach also presents some limitations:

- The case study relies on a relatively small proof-of-concept dataset consisting of five suppliers and three evaluation periods. While sufficient for demonstrating the operation of the proposed framework, larger industrial datasets are required to further evaluate scalability, predictive stability, and generalizability.
- Selecting an appropriate value for the alpha parameter requires careful adjustment.
- Continuous supervision is necessary to ensure that the model remains effective when conditions evolve over time.

5. Conclusion and Future Research Directions

A limitation of this study was the small size of the dataset, with information from only a few vendors and a limited time frame. In the first stage of our method, we applied a simple linear fusion approach, reducing the model's flexibility. SHAP-based explainable random forest is the only machine learning module available. More advanced models, such as LSTM and XGBoost, can be used to improve predictive performance. The framework should be validated in future research with actual industrial procurement data to test the generalizability and applicability of the framework. Second, other machine learning algorithms such as XGBoost and LightGBM ,can be tried to see if they have better predictive performance and stability of weights. Third, online learning methods can be integrated to facilitate the continuous adaptation in rapidly changing supply chain environments. Furthermore, the combination of fuzzy logic could improve the framework's capacity to deal with uncertainty and fuzzy expert judgments. Lastly, further studies could explore automatic optimization techniques for the alpha (α) parameter, enabling a more systematic compromise between expert knowledge and data-driven learning.

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