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Original Article

Integrating Human Reliability into Supplier Evaluation: A Cross-Layer Decision-Making Framework

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Abstract - *Supply chain decision-making often overlooks the influence of human reliability, even though judgment errors during supplier evaluation can significantly alter allocation outcomes. This paper presents a two-layer framework that addresses this limitation by combining Performance-Shaping Factors (PSFs) with human error modeling in supplier assessment processes. The first layer quantifies the probability and impact of human errors using a fuzzy set approach based on PSFs. These adjustments are then integrated into the second layer, where a multi-objective optimization model determines the most suitable supplier allocations. The framework is tested through an applied case study, which demonstrates how incorporating human reliability considerations leads to more consistent supplier scoring and improved resource distribution. This approach aims to support more grounded and adaptive decisions in complex procurement environments.*

Keywords - *Performance Shaping Factors (PSFs), Supplier selection, Multi-objective optimization, Decision-making framework, Supply Chain Management, Human error mitigation.*

1. Introduction

Recent developments in industrial systems-particularly the emergence of Industry 5.0-have brought renewed attention to integrating human capabilities alongside advanced technologies. While Industry 4.0 largely emphasized automation and digital connectivity, the focus has shifted toward approaches that value human judgment, collaboration, and sustainable practices [1]. This shift reflects the increasing complexity of supply chain structures, where decision-making must remain flexible and responsive to technological changes and human-related uncertainties [2–4]. In such an environment, it is crucial to recognize that purely technology-driven solutions are insufficient; human factors are equally important in ensuring robust operations. In this evolving context, selecting suppliers becomes more critical than ever. Supplier choices directly affect key performance metrics such as cost efficiency, responsiveness, and customer satisfaction [5]. Organizations have traditionally emphasized tangible criteria like cost, delivery, and quality factors central to supplier evaluation [6]. However, emerging human-centric paradigms of Industry 5.0 have high- lighted the need to incorporate human reliability into supplier assessment processes [7]. In practice, this means acknowledging that the people who perform supplier evaluations can introduce variability and bias. Failing to consider the reliability of human decision-makers can undermine the consistency of supplier scoring and introduce unforeseen risks in supply chain decisions. Performance Shaping Factors (PSFs) play a pivotal role in influencing human reliability during supplier evaluation, directly impacting the consistency and accuracy of decision-making [8, 9]. PSFs encompass aspects such as training adequacy, workload, task complexity, and the availability of decision-support systems, which significantly shape an evaluator's ability to make informed and reliable judgments. When these human factors are overlooked, the likelihood of evaluation errors increases. For example, an overburdened or poorly trained procurement officer may misjudge a supplier's performance, leading to suboptimal supplier selections, reduced operational efficiency, and heightened risks within the supply chain [10, 11]. Human Reliability Analysis (HRA) techniques have long been used in other high-risk domains (such as nuclear energy and aviation) to predict and mitigate human error. Yet, despite the clear importance of human reliability, traditional supplier evaluation models rarely integrate these insights in a dynamic way. Most multi-criteria decision-making frameworks in procurement still assume that human inputs are static and error-free, an assumption that often does not hold in real-world settings. Existing research in this area has been largely fragmented: some studies concentrate on modeling or predicting human error probabilities in isolation [12], while others optimize supplier selection using conventional criteria and assume consistent human judgment throughout. Even the few recent approaches introducing PSFs into the evaluation process [13] do not fully feed those human reliability insights into the supplier allocation decision. This gap in the literature points to the need for a more holistic decision-making framework that can dynamically integrate human reliability factors into supplier evaluation and selection. To address this gap, our study proposes a novel two-layer decision-making framework that explicitly incorporates human reliability considerations into the supplier evaluation and allocation. In contrast to prior works focusing solely on predicting human error or treating supplier selection as a purely technical optimization task, our approach bridges these domains by integrating a human factors model with a traditional supplier decision model.

The framework is organized into two interconnected layers. Layer 1 (Evaluation Adjustment): We develop a fuzzy logic-based PSF modeling tool that quantifies the probability and impact of human errors on supplier evaluation criteria. This fuzzy PSF model considers the various Performance Shaping Factors, translating subjective assessments like “high workload” or “low training” into adjusted scores for each supplier criterion. Layer 2 (Supplier Allocation): We then embed these adjusted, more realistic criteria scores into a multi-objective optimization model for supplier allocation. In this layer, we solve a supplier selection and allocation problem that seeks to maximize overall performance (across objectives such as cost, delivery time, and innovation) while explicitly accounting for the human-error-adjusted scores from Layer 1. By linking the fuzzy human reliability model with the optimization process, the framework ensures that insights about evaluator reliability directly inform the final supplier allocation decisions. This cross-layer integration of HRA into multi-criteria decision-making is what distinguishes our approach. It addresses the inherent uncertainties in human judgment and highlights the critical interplay between human reliability and supplier performance in a dynamic way. Ultimately, the proposed framework yields a more robust and realistic supplier evaluation process, leading to more consistent supplier rankings, better-informed resource distribution, and improved risk mitigation in complex procurement environments. (As a validation, we demonstrate these benefits through an applied case study, showing that incorporating human reliability leads to significantly more stable decision outcomes, without sacrificing other performance goals.)

2. Literature Review

Building on the introduction’s emphasis on human reliability, we now examine how this concept has been studied and applied in decision-making systems, especially within supply chain management. First, HRA has a long history of helping practitioners anticipate and mitigate errors in high-risk domains. Classic methods such as the Technique for Human Error Rate Prediction (THERP) [14] and the Human Error Assessment and Reduction Technique (HEART) [15] provide structured, quantitative estimates of human-error likelihood. These techniques proved their worth in nuclear power, aviation and healthcare, where even small lapses can have catastrophic consequences [16, 17]. Recognizing this track record, recent work has explored adapting HRA to supply chains: Rodriguez-Perez [12] demonstrated that HRA can pinpoint evaluation tasks most vulnerable to error, enabling targeted training or system improvements. Complementing this, dynamic Bayesian network models capture evolving dependencies between human errors and operational performance, dating error probabilities in real time as conditions change [18, 19].

A central challenge in applying HRA to supplier evaluation lies in the subjectivity and uncertainty of PSFs—for example, how to quantify “high workload” or “moderate training” when expert opinions diverge. Fuzzy Set Theory (FST) offers a natural remedy by converting linguistic assessments into quantitative measures. Gholamizadeh et al. successfully applied fuzzy logic to weight PSFs and adjust human-error probabilities in a supply chain context, blending qualitative judgments with robust numerical analysis [13, 20]. In parallel, Arioglu et al. constructed a Bayesian-fuzzy hybrid network to visualize interdependencies among PSFs and their joint impact on error rates during supplier evaluations [21]. These hybrid frameworks—combining FST, Bayesian inference, and other probabilistic models—have shown promising improvements in modeling the multi-dimensional nature of human reliability [22]. Despite these methodological advances, integrating human reliability insights into Multi-Criteria Decision-Making (MCDM) for supplier selection remains partial. While machine learning–based HRA frameworks (e.g. ANNHRA with RSM and SHERPA) can identify the most influential PSFs and reduce computational overhead [23], and MCDM techniques like TOPSIS, VIKOR or AHP excel at ranking alternatives under fixed criteria [24–26], few approaches truly close the loop. Cui et al. [27] enhanced MCDM stability with a Monte Carlo simulation, yet still treated human-error adjustments as an upstream input rather than weaving them directly into the optimization. Most supplier-evaluation models continue to assume static, error-free human inputs or introduce PSFs without fully feeding the resulting reliability measures into allocation decisions. This fragmentation underscores the need for a holistic, cross-layer framework that dynamically integrates fuzzy-based PSF modeling, probabilistic error quantification, and multi-objective supplier allocation in a single, coherent process. In summary, the current state of the literature reveals three main gaps:

1. Most supplier selection models ignore the variability introduced by human factors.
2. HRA and PSF studies often stop at error prediction, without feeding those insights into allocation models.
3. No comprehensive framework unites fuzzy-based PSF analysis, probabilistic error modeling, and multi-objective supplier allocation.

To address these gaps, the present study introduces a cross-layer decision-making framework that:

- Integrates PSF-driven human-error quantification with traditional supplier-evaluation criteria;
- Adjusts supplier scores based on error probabilities derived via fuzzy logic;
- Embeds these dynamic adjustments within a multi-objective optimization model to produce robust, adaptable supplier allocations.

3. Human Error Analysis and Optimal Supplier Allocation

This section concentrates on identifying and quantifying human errors and their respective contributions to inaccuracies in supplier evaluation. These errors are shaped by various PSFs representing the critical variables influencing human reliability. The methodology is implemented in two distinct phases.

3.1. Selection of PSFs and Modeling Human Errors

3.1.1. Selection of PSFs

In manufacturing, selecting PSFs is crucial for identifying the most influential human performance variables. These factors encompass critical dimensions such as training, task complexity, and environmental conditions, all of which have a direct impact on decision-making and reliability. Drawing on a comprehensive review of academic literature and domain expertise [28–36], Table 1 summarizes the PSFs evaluated in this study.

Table 1. Performance Shaping Factors (PSFs) for the manufacturing industry

PSF	Name	Description
SF1	Training Adequacy	The level of training provided to workers affects performance and error rates.
SF2	Task Complexity	The complexity of tasks assigned to workers influences the likelihood of errors.
SF3	Stress Levels	Psychological pressure experienced by workers affects their focus and decision-making.
SF4	Decision-Support Systems	Availability and usability of tools that assist in decision-making processes.
SF5	Environmental Conditions	Noise, lighting, and ergonomics influence worker comfort and reliability.
SF6	Workload	The amount of work assigned to an individual affects efficiency and error propensity.
SF7	Team Dynamics	The quality of interactions and communication among team members influences collaborative outcomes.
SF8	Safety Culture	Organizational commitment to Safety, compliance, and continuous improvement.
SF9	Operator Fatigue	Physical or mental exhaustion resulting from extended work hours or insufficient rest.
SF10	Procedural Clarity	The clarity and accessibility of work instructions, manuals, and guidelines.

3.1.2. Weighting PSFs using Fuzzy Set Theory

Fuzzy Set Theory (FST) is a powerful method for weighting PSFs, effectively handling the uncertainty and subjectivity inherent in human judgment [13, 20]. In evaluating PSFs, experts often rely on linguistic terms such as ”high importance” or ”moderate influence,” which are inherently imprecise. FST provides a systematic framework to transform these qualitative assessments into quantitative values, enabling a structured and reliable analysis.

Expert Evaluation and Input Collection

For this study, three decision-makers with substantial expertise in supplier evaluation and operational performance were selected:

- Decision-Maker 1 (DM1): A supply chain management specialist with 6 years of experience.
- Decision-Maker 2 (DM2): A quality management expert with 8 years of experience.
- Decision-Maker 3 (DM3): A logistics manager with 11 years of experience.

Each decision-maker evaluated the PSFs using linguistic terms (e.g., ”Low,” ”Medium,” ”High”) to express their perceived importance. These evaluations were collected through a structured questionnaire to ensure consistency and systematic input (see Figure 1). Table 2 shows the conversion of linguistic terms into triangular fuzzy numbers, facilitating numerical representation of qualitative inputs, and Table 3 presents the questionnaire results provided by the three decision-makers, expressed as fuzzy numbers.

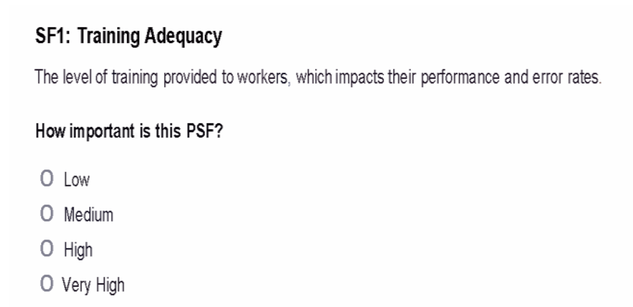

Fig. 1 Part of the questionnaire for PSF evaluation

Table 2. Conversion of linguistic variables into triangular fuzzy numbers

Linguistic Term	Triangular Fuzzy Number (a, b, c)
Low	(0.0, 0.1, 0.3)
Medium	(0.2, 0.5, 0.8)
High	(0.6, 0.8, 1.0)
Very High	(0.8, 1.0, 1.0)

Table 3. PSFs evaluations by three decision-makers with corresponding fuzzy numbers

PSF ID	Decision-Maker 1	Decision-Maker 2	Decision-Maker 3
SF1	(0.6, 0.8, 1.0)	(0.2, 0.5, 0.8)	(0.8, 1.0, 1.0)
SF2	(0.2, 0.5, 0.8)	(0.6, 0.8, 1.0)	(0.6, 0.8, 1.0)
SF3	(0.0, 0.1, 0.3)	(0.2, 0.5, 0.8)	(0.6, 0.8, 1.0)
SF4	(0.6, 0.8, 1.0)	(0.8, 1.0, 1.0)	(0.6, 0.8, 1.0)
SF5	(0.2, 0.5, 0.8)	(0.0, 0.1, 0.3)	(0.2, 0.5, 0.8)
SF6	(0.6, 0.8, 1.0)	(0.2, 0.5, 0.8)	(0.6, 0.8, 1.0)
SF7	(0.2, 0.5, 0.8)	(0.2, 0.5, 0.8)	(0.6, 0.8, 1.0)
SF8	(0.8, 1.0, 1.0)	(0.6, 0.8, 1.0)	(0.8, 1.0, 1.0)
SF9	(0.0, 0.1, 0.3)	(0.2, 0.5, 0.8)	(0.2, 0.5, 0.8)
SF10	(0.2, 0.5, 0.8)	(0.2, 0.5, 0.8)	(0.6, 0.8, 1.0)

Fuzzy Set Theory Framework

The following definitions outline the key elements of the FST framework used for PSF weighting:

Fuzzy Set: A fuzzy set A in the universe of discourse X is defined as:

$$A = \{(x, \mu_A(x)) \mid x \in X,\ \mu_A(x) \in [0,1]\}$$

Where

- X : Represents the range of possible evaluations for a PSF ("Low" to "Very High").
- $\mu_A(x)$: Denotes the membership degree x in the fuzzy set A, reflecting the extent to which a particular PSF evaluation belongs to the fuzzy set.

Membership Function

The membership function is essential for quantifying linguistic evaluations. A commonly used function is the triangular membership function. The graphical representation, depicted in Figure 2, illustrates the extent of membership μ_A and is interpreted as:

$$\mu_A(x) = \begin{cases} \frac{x-a}{b-a}, & a \le x \le b, \\ \frac{c-x}{c-b}, & b \le x \le c, \\ 0, & x < a \text{ or } x > c. \end{cases}$$

Where a, b, and c (as defined in Table 2) define the lower limit, peak, and upper limit of the triangular function.

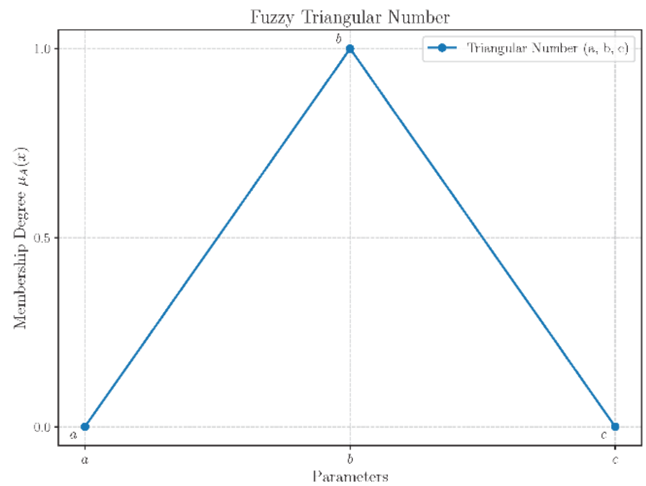

Fig. 2 Fuzzy triangular number

Aggregation of Expert Opinions

To combine the evaluations provided by multiple experts for a PSF, a weighted average approach is used:

$$\mu_A(x) = \frac{\sum_{i=1}^{k} v_i \cdot \mu_{A_i}(x)}{\sum_{i=1}^{k} v_i},$$

Where:

- kTotal number of experts.
- v_iWeight assigned to the i-th expert, reflecting their expertise or reliability.
- $\mu_{A_i}(x)$ Membership degree assigned by the i-th expert for the PSF under evaluation.

Defuzzification

Defuzzification converts the aggregated fuzzy set into a crisp value to facilitate ranking and weight assignment. One commonly used method is the centroid method:

$$z^* = \frac{\int x \cdot \mu_A(x)dx}{\int \mu_A(x)dx},$$

Where z^* does the crisp score represent the importance of the PSF?

Weight Assignment

The final weight w_j for each PSF is determined by normalizing the defuzzified scores:

$$w_j = \frac{z_j^*}{\sum_{j=1}^{m} z_j^*},$$

Where:

z_j^* Defuzzified value for PSF j.

m: Total number of PSFs.

Prioritization of PSFs

The prioritization step involves ranking the PSFs based on their calculated weights w_j, which reflect their relative importance. This process ensures that the PSFs with the highest impact are identified and retained for further analysis. Table 4 presents the results of this step.

Table 4. Aggregation, defuzzified scores, and normalized weights of PSFs (descending order of importance)

PSF ID	Aggregated Fuzzy Number	Defuzzified Score	Normalized Weight
SF8	(0.733, 0.933, 1.0)	0.889	0.141
SF4	(0.667, 0.867, 1.0)	0.844	0.134
SF1	(0.533, 0.767, 0.933)	0.744	0.118
SF2	(0.467, 0.700, 0.933)	0.700	0.111
SF6	(0.467, 0.700, 0.933)	0.700	0.111
SF7	(0.333, 0.600, 0.867)	0.600	0.095
SF10	(0.333, 0.600, 0.867)	0.600	0.095
SF3	(0.267, 0.467, 0.700)	0.478	0.076
SF5	(0.133, 0.367, 0.633)	0.378	0.060
SF9	(0.133, 0.367, 0.633)	0.378	0.060

From the prioritization process, we identified the top six PSFs that collectively capture 71% of the total importance based on their normalized weights. These factors are SF8 (Safety Culture), SF4 (Decision-Support Systems), SF1 (Training Adequacy), SF2 (Task Complexity), SF6 (Workload), and SF7 (Team Dynamics).

By selecting these six PSFs, we ensure that the most critical factors influencing the system's performance are included in subsequent analysis while maintaining a focused and manageable scope. This threshold provides an effective balance between comprehensiveness and practical feasibility.

3.1.3. Error Probabilities and Contributions

After prioritizing the PSFs, the next step involves leveraging the selected PSFs to compute the probabilities of errors and their contributions to system inaccuracies. The probability of each error Ei is determined using the following formula:

$$E_i = \sum_{j=1}^{m} w_j P_j + \epsilon_i, \quad (1)$$

Where:

- w_j Weight of PSF j, obtained from the prioritization process.
- P_j The value of PSF j represents its current state.
- ϵ_i Residual uncertainty associated with error i, capturing any unexplained variance.

To assess the impact of each error on overall system performance, the contribution of error i is calculated as:

$$C_i = \frac{\Delta S_k(E_i)}{\sum_{i=1}^{n} \Delta S_k(E_i)}, \quad (2)$$

Where $\Delta S_k(E_i)$ is the Deviation in the Supplier's score S_k caused by error E_i, and is computed as:

$$\Delta S_k(E_i) = \sum_{j=1}^{m} E_i \cdot R_{ij} \cdot \beta_j, \quad (3)$$

where

- R_{ij} Sensitivity of criterion j to error i, indicating the level of influence of the error on specific evaluation criteria.
- β_j Weight of criterion j in the overall supplier score.

3.1.4. Quantifying the Impact of Errors and Adjusting Criteria Scores

This phase integrates the influence of human errors into the supplier evaluation process by adjusting the scores for the primary criteria: cost, delivery time, and innovation. The adjustments ensure that these scores accurately reflect the potential deviations caused by human errors.

Compute Criteria Deviations: The first step quantifies the impact of errors on each criterion by calculating the Deviation (ΔS_c). This Deviation represents the extent to which errors influence the score of each criterion and is given by:

$$\Delta S_c = \sum_{j=1}^{n} E_j \cdot C_j \cdot R_{cj}, \quad (4)$$

Where (ΔS_c) is the Deviation in the score of criterion c (cost, delivery, or innovation) due to errors.

The result of this step is a set of deviations for the three main criteria (cost, delivery, and innovation), reflecting the cumulative impact of errors on each. Adjust Criteria Scores: Using the deviations computed in the previous step, the scores for the primary criteria are adjusted to account for the influence of human errors. The adjusted score for criterion c for supplier k is calculated as:

$$S_{ck'} = S_{ck} - \Delta S_c, \quad (5)$$

Where S_{ck} is the original score of criterion c for supplier k?

3.2. Supplier Allocation Optimization

Supplier allocation optimization leverages the adjusted scores to construct a multi-objective optimization model that determines the optimal distribution of resources among suppliers. This optimization ensures that the influence of human errors is thoroughly incorporated into the supplier selection and allocation process.

3.2.1. Objective Function

The goal of the optimization model is to maximize the overall performance of the Supplier, considering cost, delivery time, and innovation criteria. The objective function is defined as:

$$Z = \sum_{k=1}^{K}\left(w_C S_{Ck} + w_D S_{Dk} + w_I S'_{ik}\right) x_k, \quad (6)$$

Where for supplier k:

- S_{Ck} Adjusted cost score.
- S_{Dk} Adjusted delivery time score.
- S'_{Ik} Adjusted innovation score, incorporating human error impacts.
- w_C, w_D, w_I Weights are assigned to cost, delivery time, and innovation, respectively.
- x_k: Allocation variable for supplier k, representing the proportion of resources allocated to supplier k.

3.2.2. Constraints

The optimization problem is subject to the following constraints to ensure feasibility and alignment with real-world operational requirements:

1. Weight Normalization: The sum of the criteria weights must equal 1.

$$w_C + w_D + w_I = 1 \quad (7)$$

2. Allocation Constraint: The total allocation across all suppliers must equal 1, with no negative allocations:

$$\sum_{k=1}^{K} x_k = 1, \quad x_k \geq 0 \quad (8)$$

3. Capacity Constraint: The quantity of products allocated to each supplier k must not exceed the Supplier's capacity C_k:

$$\sum_{j=1}^{M} x_k Q_j \leq C_k, \quad \forall k, \quad (9)$$

Where:

- Q_j: Quantity of product j to be allocated.
- C_k Maximum capacity of supplier k.

4. Delivery Time Constraint: Each Supplier's delivery time D_k must not exceed the maximum acceptable delivery time D^*:

$$D_k \leq D^*, \quad \forall k. \quad (10)$$

4. Cross-Layer Decision-Making Framework

The cross-layer decision-making framework integrates human error analysis into the supplier evaluation and allocation. The model is composed of two interconnected layers:

Layer 1: Human Error Analysis and Adjusted Criteria Scores focuses on identifying and quantifying the impact of human errors on supplier evaluation criteria and adjusting the scores accordingly.

Layer 2: Supplier Allocation Optimization utilizes the adjusted scores from Layer 1 to construct a multi-objective optimization model for determining the optimal allocation of suppliers while fully accounting for human errors.

Algorithm 1 provides a detailed outline of the steps used to implement the proposed framework.

5. Experimental Case Study

5.1. Input Data

The experimental case study demonstrates the effectiveness of the proposed methodology for supplier selection and allocation. The study evaluates the performance of four suppliers (S1, S2, S3, S4) for three strategic products (P1, P2, P3). The evaluation incorporates cost, delivery time, and innovation as the main criteria, with cost and delivery time represented as stochastic variables (mean and standard Deviation) and innovation scores expressed as fuzzy numbers. Product demand and supplier capacity are also included as constraints. The input data are summarized in Tables 5-9.

Algorithm 1 Cross-layer decision-making framework

Input: Supplier scores (S_{Ck}, S_{Dk}, S_{Ik}), Performance Shaping Factors (PSFs), product demand (D_j), and supplier capacity (C_k).
Output: Optimal supplier allocations (x_k).

Layer 1: Human Error Analysis and Adjusted Scores
Step 1.1: Identify Relevant PSFs: Select the top m PSFs using expert judgment and Fuzzy Set Theory to account for uncertainty and variability. (As in section 3.1.2)
Step 1.2: Calculate Error Probabilities. Determine the

likelihood of key errors (E_i) based on the selected PSFs using Equation 1.
Step 1.3: Quantify Error Contributions. Assess the relative impact (C_i) of each error on the supplier scores using Eq. 2.
Step 1.4: Adjust Criteria Scores Modify supplier scores (S_{Ck}, S_{Dk}, S_{Ik}) for cost, delivery, and innovation by incorporating error impacts using Eqs. 4 and 5.

Layer 2: Supplier Allocation Optimization
Step 2.1: Define the Objective Maximize supplier performance based on the adjusted scores for cost, delivery, and innovation using Eq. 6.
Step 2.2: Incorporate Constraints Ensure constraints for demand satisfaction (D_j), capacity limits (C_k), and allocation feasibility are met as defined in section 3.2.2.
Step 2.3: Solve the Optimization Problem. Compute the optimal supplier allocations (x_k).
Return: Optimal supplier allocations (x_k).

Table 5. Cost data (S_{Ck}) with mean and standard deviation (units)

Supplier/ Product	P 1	P 2	P 3
S1	50 ± 2	70 ± 3	80 ± 4
S2	52 ± 2.5	69 ± 3.5	77 ± 3
S3	51 ± 2.2	71 ± 3.2	79 ± 3.8
S4	53 ± 2.3	72 ± 3.3	78 ± 3.5

Table 6. Delivery time data (S_{Dk}) with mean and standard deviation (days)

Supplier/Product	P 1	P 2	P 3
S1	10 ± 1.2	15 ± 1.5	12 ± 1.3
S2	12 ± 1.4	14 ± 1.2	13 ± 1.1
S3	11 ± 1.0	13 ± 1.3	11 ± 1.2
S4	10 ± 1.1	12 ± 1.4	10 ± 1.0

Table 7. Innovation score data (S_{Ik}) as fuzzy numbers

Supplier/ Product	P 1	P 2	P 3
S1	(0.6, 0.8, 1.0)	(0.5, 0.7, 0.9)	(0.4, 0.6, 0.8)
S2	(0.7, 0.9, 1.0)	(0.6, 0.8, 1.0)	(0.5, 0.7, 0.9)
S3	(0.5, 0.7, 0.9)	(0.4, 0.6, 0.8)	(0.6, 0.8, 1.0)
S4	(0.8, 1.0, 1.0)	(0.7, 0.9, 1.0)	(0.5, 0.7, 0.9)

Table 8. Demand for each product

Product (P_j)	Demand (Units)
1	120
2	150
3	100

Table 9. Capacities for each supplier

Supplier (S_k)	Capacity (Units)
1	300
2	250
3	200
4	220

5.2. Supplier Allocation Results Using Cross-Layer Optimization

5.2.1. Error Probabilities and Contributions

We define three common errors (E1, E2, E3) in this study and establish their relationship with the top six PSFs.

Definition of Errors (Ei)

- E_1: Cost-related Error: Represents inaccuracies in cost evaluation due to factors like insufficient training (SF1) and task complexity (SF2). These factors directly affect the precision of cost estimation during supplier evaluations.
- E_2: Delivery-related Error: Reflects errors in estimating delivery times, influenced by workload (SF6) and team dynamics (SF7). These factors impact the reliability of delivery performance assessments.
- E_3: Innovation-related Error: Captures inaccuracies in innovation score evaluation, driven by decision-support systems (SF4) and safety culture (SF8). These factors shape the consistency of decision-making in assessing innovation capabilities.

Relationship Between Errors and PSFs: Each error (Ei) is modeled as a function of the PSFs most relevant to its nature. The fuzzy aggregated values (Pj) of these PSFs, combined with their weights (wj), determine the probability of each error.

Using the aggregated fuzzy values and weights of the top PSFs from Table 4, we calculate the probabilities of E1, E2, and E3 using equation 1, and the corresponding contributions Ci using equation 2. The calculated error probabilities and contributions are presented in Table 10.

Table 10. Calculated error probabilities and contributions

Error	Probability (E_i)	Contribution (C_i)
E1	(0.115, 0.169, 0.213)	0.33
E2	(0.084, 0.135, 0.185)	0.25
E3	(0.192, 0.248, 0.275)	0.42

5.2.2. Initial and Adjusted Scores

Calculating adjusted scores integrates the impact of human errors (E_i) and their contributions (C_i) into evaluating each Supplier.

Table 11. Initial and adjusted scores for each supplier

Supplier	Cost (S_{Ck})		Delivery (S_{Dk})		Innovation (S_{Ik})	
	I	A	I	A	I	A
S1	50	48.7	9	8.8	0.6	0.54
S2	52	50.5	12	11.6	0.7	0.63
S3	51	49.9	11	10.5	0.5	0.42
S4	55	53.1	10	9.6	0.8	0.77

The adjusted scores for cost, delivery, and innovation are calculated using equation 5 to reflect the deviations caused by errors (calculated based on equation 4), providing a more accurate assessment of supplier performance. The initial and adjusted scores for each Supplier and criterion are summarized in Table 11.

5.2.3. Optimization Results

The final step in the methodology uses the adjusted scores for cost, delivery, and innovation to determine the optimal allocation of resources among suppliers. This is achieved using the multi-objective optimization model that balances the trade-offs between the three criteria in equation 6, subject to the constraints defined in section 3.2.2. Table 12 presents the mean allocations (x_k) for each Supplier under two scenarios:

- Without Errors: The initial scores are used in the optimization without adjusting for human errors.
- With Errors: The adjusted scores are used, incorporating the effects of human errors on supplier performance.

Table 12. Mean allocations for each supplier

Supplier (S_k)	Allocation Without Errors	Allocation With Errors
1	0.28	0.27
2	0.24	0.26
3	0.22	0.20
4	0.26	0.27

The results of comparing mean allocations for each Supplier, as illustrated in Figure 3, reveal the nuanced impact of incorporating human errors into the supplier selection and allocation process. The reallocation of resources is evident as the inclusion of human errors causes minor but meaningful shifts in the mean allocations for all suppliers.

These changes signify the robustness of the cross-layer optimization model, which adapts to reflect adjustments in criteria scores due to the impact of errors.

Supplier-Specific Observations

The increase from 0.24 to 0.26 indicates that S2 benefited from the adjustments. This relative gain suggests that S2's delivery and innovation evaluations were less sensitive to fluctuations in PSFs, such as workload and decision-support usability. In other words, even when human assessors experienced increased cognitive load or variation in tool support, the adjusted scores for S2 remained comparatively stable, strengthening its attractiveness in the optimized allocation. Conversely, the drop for S3 from 0.22 to 0.20 highlights its vulnerability to error-induced deviations, particularly in the innovation criterion, where subtle biases or misinterpretations of supplier proposals can lead to disproportionate score reductions. This sensitivity may stem from a heavier reliance on qualitative judgments or more complex innovation metrics, which amplify the effect of PSFs such as training adequacy and procedural clarity.

These allocation shifts, though quantitatively small, carry significant qualitative meaning. For S2, the capacity to absorb human-error variability points to a supplier evaluation profile characterized by clear, measurable performance indicators. In contrast, S3's steeper decline underlines the need for greater consistency in how innovation is assessed, suggesting that standardizing evaluation templates or enhancing training around innovation metrics could reduce score volatility. Moreover, the fact that all suppliers experienced adjustments shows that human errors are not random but affect every part of the evaluation, from reading data to assigning scores. Managers must consider these facts because it turns supplier selection from a fixed checklist into a flexible process where human factors are key to managing risk.

Fig. 3 Comparison of mean allocations for each supplier

Strategic Insights

The shifts in allocation suggest concrete steps for improving both supplier performance and internal processes. For example, S3's lower share after accounting for human errors indicates that its innovation scores are especially sensitive to how evaluators interpret criteria. Working more closely with procurement teams to define and standardize those innovation metrics, such as clear scoring rubrics, should reduce subjective variation. In contrast, S2 and S4 maintain more stable allocations, implying that their documentation and presentations match well with key PSFs.

5.2.4. Sensitivity Analysis

The sensitivity analysis evaluates the impact of varying weights assigned to the three evaluation criteria (Cost, Delivery, and Innovation) on the mean allocations for suppliers (S1, S2, S3, S4). We define four scenarios as follows:

- Sc1: Baseline (w_C = 0.4, w_D = 0.3, w_I = 0.3)
- Sc2 : High Cost (w_C = 0.6, w_D = 0.2, w_I = 0.2)
- Sc3 : High Delivery (w_C = 0.2, w_D = 0.6, w_I = 0.2)
- Sc4 : High Innovation (w_C = 0.2, w_D = 0.2, w_I = 0.6)

From Table 13, we observe that each Supplier's share responds predictably to shifts in strategic emphasis:

- When cost dominates (w_C = 0.6), S_1 gains the most (+0.01 from baseline), reflecting its competitive pricing, while S_2 and S_4 lose ground.
- Under a delivery focus (w_D = 0.6), S_2 jumps to 0.28, confirming its superior delivery performance; S_1 and S_3 correspondingly decrease.
- With innovation prioritized (w_I = 0.6), S_3 increases to 0.24, indicating that its strength in innovation becomes more valuable, even though it is sensitive to human-error adjustments in other scenarios.

Table 13. Mean allocations for each Supplier under different weight scenarios

Scenario	S1	S2	S3	S4
Sc1	0.27	0.26	0.20	0.27
Sc2	0.28	0.24	0.22	0.26
Sc3	0.24	0.28	0.22	0.26
Sc4	0.23	0.26	0.24	0.27

To quantify each Supplier's responsiveness, we calculate the allocation elasticity with respect to each criterion weight:

$$E_{k,C} = \frac{\Delta x_k}{\Delta w_C}, \quad E_{k,D} = \frac{\Delta x_k}{\Delta w_D}, \quad E_{k,I} = \frac{\Delta x_k}{\Delta w_I}.$$

For example,$E_{2,D} = (0.28 - 0.26)/(0.6 - 0.3) \approx 0.067$ confirming S2's high sensitivity to delivery weight. In contrast, $E_{1,C} \approx 0.033$S1 is less elastic to cost changes, underscoring its stable pricing advantage. Further, mapping allocations over a continuous range of weights (e.g. a heatmap over (w_C, w_D)) $w_I = 1 - w_C - w_D$reveals non-linear thresholds. Small increases $w_I$beyond 0.5 trigger a rapid shift from S3 to S4, suggesting a tipping point where innovation leadership outweighs other factors.

Implications for Decision-Making: These insights enable procurement managers to:

- Set criteria weights with a clear understanding of each Supplier's strategic fit and vulnerability to human error variability.
- Identify weight thresholds that produce disproportionate allocation shifts, informing risk-averse strategies (e.g. avoiding abrupt reassignments when $w_I$crossing 0.5).
- Balance robustness and agility by combining suppliers with complementary elasticities. For instance, pairing a supplier whose allocation is stable under cost-weight changes with another whose allocation responds strongly to delivery-weight shifts, thereby hedging against evolving strategic priorities.

6. Discussion and Conclusions

The cross-layer decision-making framework introduced in this study provides an innovative approach to integrating human error analysis into supplier evaluation and allocation processes. Traditional supplier evaluation methods often neglect the critical influence of human reliability factors, which can lead to suboptimal decisions, operational inefficiencies, and increased risks.

By incorporating PSFs into the evaluation process, this framework quantifies the probabilities and impacts of human errors, resulting in a more realistic and robust assessment of suppliers. The findings of this study underline the critical role of human factors in supply chain decision-making. Human errors, shaped by PSFs, directly impact supplier evaluation and allocation processes, and addressing these factors provides decision-makers with a structured approach to mitigate their effects.

This improves the reliability and efficiency of supply chain operations and enhances adaptability in environments characterized by high complexity and uncertainty. Several opportunities for future research and development emerge from this study. The framework could be extended to incorporate dynamic modeling of PSFs, enabling adjustments over time to reflect changes in operational conditions, evaluator performance, or supplier reliability.

Integrating machine learning and artificial intelligence tools offers another promising avenue, enhancing error probability estimation, automating PSF identification, and improving real-time decision-making capabilities. Expanding the framework to include sustainability metrics, such as carbon footprint, waste reduction, and ethical sourcing, would align supplier evaluations with global sustainability goals and organizational priorities. Developing real-time decision-support systems based on the framework could enhance its utility in dynamic and fast-paced supply chain environments. Additionally, applying the framework to a broader range of industries and supply chain contexts would validate its versatility and uncover new areas for refinement. In conclusion, the integration of human reliability analysis into supplier evaluation processes represents a significant advancement in addressing the complexities of modern supply chain management. By accounting for human errors and their underlying factors, the proposed framework bridges the gap between theoretical models and practical decision-making. Its ability to dynamically adjust supplier scores and optimize resource allocations gives decision-makers a powerful tool to enhance efficiency, reliability, and adaptability. Continued development of this framework, including its integration with emerging technologies and sustainability considerations, will ensure its relevance and impact in addressing the challenges of future supply chains.

Data Availability Statements

The datasets generated and analyzed during this study are available from the corresponding author upon reasonable request.

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