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Assessment and Selection of Suppliers in Uncertain Conditions: Hybrid Multi-Criteria Decision-Making Approach

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Abstract

This study proposes a hybrid model for optimizing supplier selection by addressing both quantitative and qualitative evaluation criteria. The framework integrates the factor relationship (FARE) method and grey relational analysis (GRA) to provide a robust and systematic approach to supplier assessment. The methodology is implemented in two key stages: first, the FARE method is employed to determine the relative importance of evaluation criteria, ensuring an accurate representation of decision-making priorities. In the second stage, GRA is applied to evaluate and rank suppliers based on these weighted criteria, enabling a comprehensive comparison. To demonstrate its practicality, the proposed model is validated through a case study in the chemical industry, showcasing its real-world applicability and effectiveness. Furthermore, the model's performance is compared with findings from previous studies, highlighting its superior capability in addressing complex supplier selection scenarios. This work offers valuable insights for decision-makers seeking reliable and efficient methods for supplier evaluation and selection.

Categories: Decision Support, Strategic Supply Chain Management
Keywords: supplier evaluation, supplier selection, uncertainty, gra, fare method

Introduction

The supply chain is a dynamic and interconnected network of entities that spans from raw material suppliers to end customers, forming the backbone of industrial operations. This network addresses numerous critical challenges, with supplier assessment and selection playing a pivotal role in determining the efficiency and success of the entire supply chain. One of the key concerns in this context is the cost of raw materials, which often accounts for the largest expense in manufacturing processes. Studies have shown that approximately 30% of production defects are attributed to the supply of substandard materials [1], emphasizing the importance of precise and effective supplier selection to mitigate these risks.

Selecting an appropriate supplier is a strategic decision that significantly influences operational efficiency, cost reduction, product quality, and customer satisfaction. Beyond reducing risks, accurate supplier selection enhances profitability, streamlines production processes, and fosters long-term partnerships within the supply chain. However, the supplier selection process is inherently complex, as it requires the evaluation of a wide range of criteria, encompassing both quantitative factors (e.g., cost, delivery time, and quality metrics) and qualitative aspects (e.g., reputation, sustainability practices, and innovation capabilities).

In real-world scenarios, the supplier selection process is further complicated by the presence of incomplete, imprecise, or ambiguous information. Decision-makers often face challenges in synthesizing diverse data sources, prioritizing conflicting criteria, and addressing the uncertainty inherent in such evaluations. These complexities necessitate the development of advanced decision-making frameworks that can effectively handle uncertain and vague information. This paper presents a hybrid approach to address these challenges and optimize supplier selection. This study not only provides a comprehensive framework for supplier evaluation but also contributes valuable insights for decision-makers in supply chain management, enabling them to make strategic, informed, and sustainable choices.

Literature review

The related literature is divided into supplier assessment and selection approaches, grey relational analysis (GRA) and factor relationship (FARE) applications, and hybrid approaches.

Review of Supplier Assessment and Selection Approaches

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Numerous researchers have dedicated their efforts to identifying the criteria that significantly impact supplier assessment and selection. Dickson [2] surveyed to identify the criteria influencing supplier selection, resulting in the identification of 23 significant factors. Weber et al. [3] conducted a systematic review of 74 research articles, highlighting quality, net price, production capability, delivery, technical capability, geographical location, financial position, reputation, warranty, and performance history as highly influential factors for supplier selection. Wilson [4] provided a detailed review of the comparative significance of selection criteria, emphasizing quality, price, delivery, and service as key factors. Choi and Hartley [5] compared supplier selection practices in the auto industry, identifying price, consistency (quality and delivery), reliability, service, and flexibility as highly influential factors. De Boer et al. [6] extensively reviewed decision techniques for assisting supplier selection, covering problem definition, criteria selection, supplier identification, and final selection. Ho et al. [7] conducted a thorough review of the literature published between 2000 and 2008 on the applications of various multi-criteria decision-making (MCDM) methodologies for supplier assessment and selection.

Researchers have utilized a variety of methodologies for supplier selection, including linear programming, goal programming [8], analytic hierarchy process (AHP) [9,10], analytical network process [11], data envelopment analysis (DEA) [12], genetic algorithm [13,14], artificial neural network [15], case-based reasoning [16], fuzzy logic [17], and fuzzy voting models [18]. Additionally, integrated approaches such as AHP and goal programming [8], AHP and GRA [19], fuzzy AHP (FAHP) [20-22], fuzzy DEA [22,23], fuzzy complex proportional assessment [24], ELECTRE (ELimination and Choice Translating Reality) [25], PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation) [26], and VIKOR (VlseKriterijuska Optimizacija I Komoromisno Resenje) [27] have been reported in literature. Govindan et al. [28] extensively reviewed green supplier evaluation, considering environmental factors. They identified fuzzy-based single-model approaches as commonly used by researchers. Keshavarz Ghorabaee et al. [29] reviewed the use of multiple-attribute decision-making methods for supplier selection with vague data and concluded that the AHP and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) methods were the most prevalent. Jemaa et al. [30] reviewed journal publications between 2012 and 2019 on approaches to green supplier assessment and selection, noting that the majority of methods integrated fuzzy models as MCDM tools.

Review of Grey Relational Analysis

The grey system theory [31] is a method designed to tackle problems characterized by ambiguity and uncertainty. In supplier selection problems, where linguistic variables play a crucial role in decision-making, the grey rough set theory method has been applied. This approach involves transforming linguistic variables assigned to choices into grey numbers, facilitating the selection of the most suitable supplier [32]. Çebi and Bayraktar [8] used goal programming and AHP to select suppliers for a food processing industry. They considered logistics criteria, technologic criteria, business criteria, and relationship criteria. Additionally, the GRA method has been proposed to address supplier assessment problems characterized by ambiguity and a lack of information. In this approach, criteria weights are determined using both quantitative and qualitative information, leveraging fuzzy set theory. The GRA is then employed to rank the alternatives in terms of their suitability [33]. Bhayana et al. [34] discussed a GRA model for sustainable supplier selection, illustrated through a case study in the electronics industry.

Review of Factor Relationship

Ginevicius [35] introduced the FARE method, aimed at computing criteria weights by analyzing the correlation among all criteria. Initially, domain specialists draw correlations, strengths, and trends among the sets of criteria. Using this information, the total impact of each criterion on the others is determined, providing the criteria weights. Chatterjee et al. [36] utilized the multi-attributive border approximation area comparison method to select the most suitable non-traditional machining process. They employed the FARE method to estimate criteria weights. Similarly, Girdzijauskaitė et al. [37] identified and ranked key performance indicators (KPIs) influencing the competitiveness of universities using the FARE method. Six significant KPIs were identified, and the FARE technique was employed to determine their weights.

Review of Hybrid Approaches

Yang and Chen [38] proposed a supplier assessment model for a notebook computer manufacturer, combining AHP and GRA. AHP was employed to determine criteria weights, while GRA ranked the suppliers. Similarly, Pitchipoo et al. [19] established a hybrid supplier selection model for a chemical processing industry, utilizing mutual information feature selection and AHP for criteria selection and weighting, respectively, with GRA used for supplier ranking. Prasad et al. [39] also adopted a hybrid model for vendor selection, merging fuzzy and GRA methodologies to address uncertainty and achieve a probabilistic interpretation of outcomes. Zhang and Liu [40] developed a fuzzy multi-criteria group decision-making methodology for task assignment, incorporating entropy measurement for criteria weighting and GRA for alternative ranking. In another context, Alinezad et al. [41] utilized the fuzzy AHP for criteria weighting in quality function deployment for vendor selection in a pharmaceutical firm.

Furthermore, Pang et al. [42] investigated supplier selection in low-carbon supply chains, by proposing a fuzzy-grey integrated MCDM technique, validated through a case study in the steel industry. Chang et al. [43] suggested a fuzzy GRA-based evaluation model for supplier selection in the garment industry, considering criteria such as product quality, price, order quantity, delivery time, and after-sale services.

Based on this thorough review, the following observations are made (Table 1).

Methodology	Limitation
Goal programming	Difficult to handle large number of criteria, and it does not take into account the uncertainty
AHP	Perfect consistency is very difficult, time consuming with large numbers, complexity of the pairwise comparison, challenge of consistency in decision-making, and requires high level of management involvement
ANP	Inapplicability of statistical tests
DEA	Difficult to perform statistical tests with the results
ELECTRE	Adoption of linguistic variable is difficult, and it does not take into account the uncertainty
PROMETHEE	Not able to evaluate under vagueness and uncertainty
VIKOR	Not able to evaluate under vagueness and uncertainty

TABLE 1: Limitations of existing methodologies

AHP: Analytic Hierarchy Process; ANP, Analytical Network Process; DEA: Data Envelopment Analysis; ELECTRE: Elimination and Choice Translating Reality; PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluation; VIKOR: VlseKriterijuska Optimizacija I Komoromisno Resenje

According to the analysis provided here, choosing a supplier is an MCDM process that takes into account both qualitative and quantitative data. Most of the existing methodologies are able to address the single-objective problems. Our study fills a vacuum in the supplier selection literature by investigating a new model that combines FARE and GRA approaches. This hybridization approach is used in the supplier assessment and selection domain. The FARE method is utilized to calculate criteria weights, while GRA ranks the suppliers, offering a unique perspective on supplier selection.

Research Method

The proposed methodology combines FARE method and GRA to provide a robust and systematic framework for supplier evaluation. The process is structured into two stages: first, the FARE method is employed to determine the relative importance of evaluation criteria, ensuring that the weighting process aligns with organizational priorities and decision-making objectives. This step enhances the precision and objectivity of the evaluation process by accounting for the interdependencies among criteria.

In the second stage, GRA is utilized to rank suppliers based on the weighted criteria. GRA is well regarded for its capability to handle incomplete and imprecise data, making it an ideal choice for addressing the uncertainties often encountered in supplier selection scenarios. By evaluating the closeness of each supplier to an ideal solution, GRA provides a clear and realistic ranking, facilitating informed decision-making.

The effectiveness of the proposed hybrid model is demonstrated through its application to a case study in the chemical industry, showcasing its practical utility and adaptability to real-world conditions. The industry chosen for this study deals with electroplating of automotive spares, located in Chennai, Tamil Nadu, India. This industry has been facing challenges in sourcing decision, which aligns well with the objectives of our study to address and propose solutions using our research model. Currently, the industry dealt with five suppliers for its raw materials.

Furthermore, a comparative analysis with existing methods highlights the superiority of the proposed approach in managing complex and uncertain supplier selection scenarios.

Model development

The decision problem discussed in this work contains five alternatives, represented by suppliers S1, S2, S3, S4, and S5. For the evaluation of these alternatives, the following decision criteria were considered:

1. Cost of the material

2. Quality of the supplied materials in average percentage of acceptance

3. Delivery lead time in weeks

4. Warranty given on the material in weeks

5. Capacity of production/supply

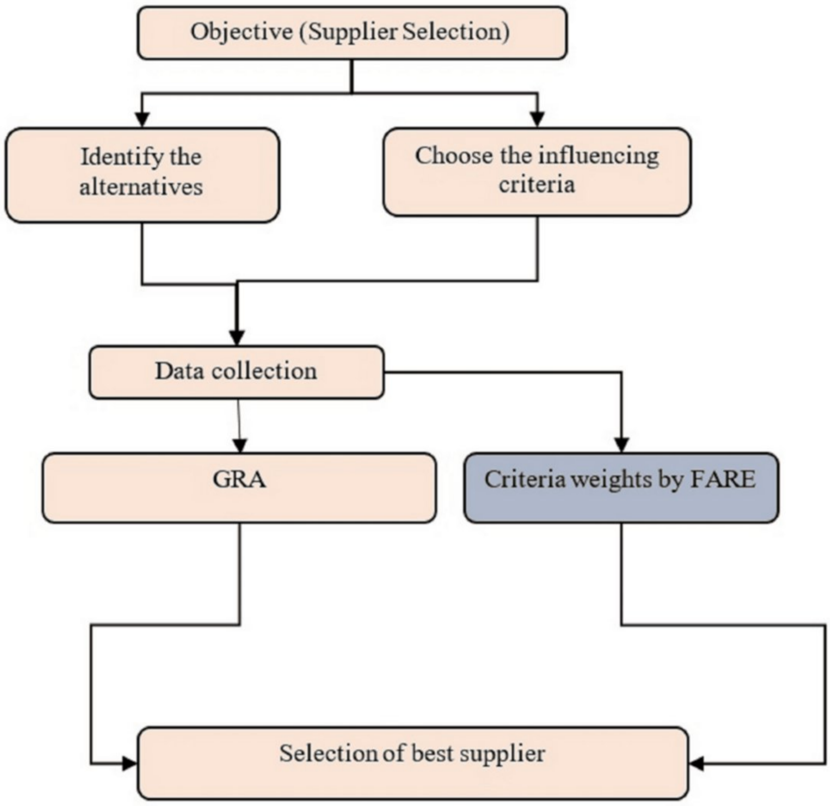

FIGURE 1: Hybrid algorithm for supplier selection

GRA: Grey Relational Analysis; FARE: Factor Relationship

The framework of the proposed methodology for the assessment and selection process is shown in Figure *1*. This paper integrates two different methods to achieve this goal. In the real-world environment, it is essential to combine expert judgment with a scientific method. To accomplish this, an expert judgment-based method (FARE) is amalgamated with a scientific method (GRA).

Grey relational analysis

The GRA procedure has the following steps [31]:

1. Identification of influencing criteria and alternatives

2. Data collection

3. Construction of criteria matrix

4. Normalization

5. Computation of the grey relational coefficient

6. Determination of the grey relational grade (GRG)

7. Selection of the best supplier

The data associated with the chosen criteria mentioned earlier for all five suppliers were gathered from the case study organization. From the collected data, the criteria matrix or data matrix (*X*) is formed, as depicted in Equation (1):

$$X = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mn} \end{bmatrix} (1)$$

where '*m*' denotes the total number of alternatives, and '*n*' denotes the total number of criteria.

The data in the data matrix are pre-processed using grey normalization. Data pre-processing transforms the actual sequences to a set of comparable sequences. Normalization can be performed as $X_i(j)$ by using Equations (2) and (3) to prevent the impact of implementing various units and to lessen the variability. Here $x_i(j)$ lies between 0 and 1. Unlike other practices, GRA takes the performance quality of the criteria into account during normalization. The criterion for which the larger value is optimal can be normalized by applying Equation (2). The others can be normalized by applying Equation (3):

$$X_i^*(j) = \frac{x_i(j) - \min x_i(j)}{\max x_i(j) - \min x_i(j)} (2)$$

$$X_i^*(j) = \frac{\max x_i(j) - x_i(j)}{\max x_i(j) - \min x_i(j)} (3)$$

where '*i*' is the alternative from 1 to *m*; '*j*' is the criteria from 1 to *n*.

From these normalized data, the grey relational coefficient is determined by applying Equation (4) to determine the correlation between the better and the actual results:

$$\gamma_i(j) = \frac{\Delta_{\min} + \Delta_{\max}}{\Delta_i(j) + \Delta_{\max}} (4)$$

where

$$\Delta_i(j) = |X_o^*(j) - X_i^*(j)| (5)$$

in which $X_o^*(j)$ = optimal value for criterion '*j*'; $X_i^*(j)$ is the normalized cell value of the *j*th criterion; $\Delta_{\min} = \min \Delta_i(j);$ $\Delta_{\max} = \max \Delta_i(j)$ and $\xi]$ = distinguished coefficient $\epsilon \in [0 \text{ to } 1]$.

After that, GRG is derived by applying Equation (6):

$$\Gamma_i = \sum_{j=1}^{n} W_j \cdot \gamma_i(j) (6)$$

where W_j = the weight of the criterion *j*.

In the present study, the criteria weights (W_j) are determined by using a methodology called the FARE method. The GRG exemplifies the degree of relationship amid the reference and comparability sequences. By using this GRG, the alternatives are ranked, and the better one is selected.

FARE method

This paper introduces FARE, a method based on expert opinions for determining criteria weights in MCDM problems [35]. In this approach, the potential impacts of all criteria are initially assessed using Equation (7):

$$P = S \cdot (n-1) \quad (7)$$

where 'P' represents the potential value of the system's criterion; 'S' represents the highest scale value of the assessment from Table 2; 'n' represents the number of criteria.

Subsequently, the domain specialists prioritized all the criteria depending on their significance. After that, the correlation between all the criteria is calculated depending on the priority/ratings presented in Table 2.

S. No.	Produced Effect	Rating (In Points)
1	No effect	1
2	Very poor influence	2
3	Poor influence	3
4	Lesser than average influence	4
5	Average influence	5
6	Greater than average influence	6
7	Strong influence	7
8	Very strong influence	8
9	Closer to absolute influence	9
10	Absolute influence	10

TABLE 2: Rating of criteria based on expert's opinion

Source: [35]

The criterion with the lowest rank order has the least influence on the criteria having top order ratings, and, consequently, it must pass on a greater part of its potential influence to them. The criteria's impression (a_i) on the key criterion is calculated, and, next, this effect is converted using Equation (8):

$$a_{1i} = S - \tilde{a}_{1i} \quad (8)$$

where 'a_i' denotes the effect of the ith criterion on the first key criterion; '$\tilde{a}_i$' denotes the fraction of the potential impact of the ith criterion that is transferred to the key criterion.

In addition to the confidence limits of subgroups, the overall effect of the process can also be calculated using data presented in a matrix form. A decision matrix is consistent and steady if the total number of interactions between criteria with a positive sign is equal to the total number of interactions between all criteria with a positive sign, negative, that is, if their number is equal [35]. Next, the overall influence P_i is determined by applying Equation (9):

$$P_i = \sum_{i=1}^{m} a_{ij}, \quad j \neq i \quad (9)$$

Then, the overall potential (Equation [10]), which is essential for computing the weights of all criteria, can be determined by applying the data available in the foremost row in the matrix, thus the computation of the remaining rows in the matrix is redundant:

$$P_i = P_1 - m \cdot a_{1i} \quad (10)$$

where 'P_i' is the overall influence of the ith criterion.

To conclude, the criteria weights can be computed using Equation (11):

$$\omega_i = \frac{P_i^f}{P_S} = \frac{P_1 - ma_{1i} + S(m-1)}{mS(m-1)} \quad (11)$$

where 'P_S' is the overall potential of a criteria set, which is calculated by applying Equation (12), and P_i^f represents actual overall impact of the *i*th criterion of the model, and the same is determined by applying Equation (13):

$$P_S = m \cdot P = m \cdot S(m-1) \quad (12)$$

$$P_i^f = P_i + P \quad (13)$$

Results

In the present paper, the success of the suggested model is demonstrated by an industrial case study implemented in a chemical processing industry located in the southern part of India. In this research, the purchase of raw materials from multiple sources is considered. The data pertaining to organization particulars, process particulars, particulars about the suppliers, influencing criteria, and the decision-maker's opinion on criteria were gathered from the industry.

Determination of criteria's weights by FARE

The potential influence of the criteria is calculated as 40 using Equation (7). Next, all the criteria are graded by domain specialists (decision-makers in that industry and similar industries) based on their importance, and their average ranks are presented in Table 3. From the ratings of the criteria, using Table 2, the relationships between the criteria are identified and provided in Table 4. By using Equation (8), the potential impact transmitted to the first key criterion is calculated and presented in the same table.

Criteria	Cost (Co)	Quality (Q)	Delivery (D)	Warranty (W)	Capacity (Ca)
Rank	3	1	2	4	5

TABLE 3: Rank of the criteria by the experts

Criteria	Correlation of the First Key Criterion With Other System's Criteria					Potential Influence Transmitted to the First Key Criterion					Sum
	Co	Q	D	W	Ca	Co	Q	D	W	Ca	
Co		-4	-2	3	6		-6	-8	7	4	-3
Q	4		2	4	6	6		8	6	4	24
D	2	-2		2	4	8	-8		8	6	14
W	-3	-4	-2		2	-7	-6	-8		8	-13
Ca	-6	-6	-4	-2		-4	-4	-6	-8		-22

TABLE 4: FARE calculations

Co: Cost; Q: Quality; D: Delivery; W: Warranty; Ca: Capacity; FARE: Factor Relationship

Finally, using Equations (9)-(11), the criteria weights are calculated and presented in Table 5.

Criteria	Actual Total Impact	Criteria Weights (w_j)
Cost	37	0.185
Quality	64	0.320
Delivery	54	0.270
Warranty	27	0.135
Capacity	18	0.090

TABLE 5: Actual impact and criteria weights

Discussion

Ranking of the suppliers

The data collected for all alternatives are shown in Table 6 (decision-making matrix). This is referred to as the criteria matrix. The reference series of X0 is formulated using the optimal values of all the criteria:

X0 = (0.932, 12, 2308.814, 4, 57.67)

Next, preprocessing of the data is performed to reduce the variability in the data ranges through normalization of the raw data. The normalized data are presented in Table 6.

	Original Data					Normalized Data					Grey Relational Coefficient (γ)					GRG
Supplier	Q (%)	D (Weeks)	Co (INR)	W (Weeks)	Ca (Units)	Q	D	Co	W	Ca	Q	D	Co	W	Ca	
S1	0.868	13	2432.637	4	39.00	1.000	0.500	0.171	0.000	1.000	1.000	0.971	0.999	0.833	1.000	0.970
S2	0.898	12	2516.074	3	48.33	0.539	0.000	0.286	0.500	0.500	0.623	0.944	0.999	0.909	0.994	0.851
S3	0.923	14	2700.748	3	48.83	0.132	1.000	0.540	0.500	0.473	0.422	1.000	0.999	0.909	0.994	0.802
S4	0.932	12	3033.984	2	57.67	0.000	0.000	1.000	1.000	0.000	0.382	0.944	1.000	1.000	0.988	0.786
S5	0.889	14	2308.814	2	57.67	0.671	1.000	0.000	1.000	0.000	0.735	1.000	0.999	1.000	0.988	0.914

TABLE 6: Grey relational analysis

Q: Quality; D: Delivery; Co: Cost; W: Warranty; Ca: Capacity; GRG: Grey Relational Grade; INR: Indian Rupee

During normalization, criteria such as quality, warranty, and capacity are normalized by applying the larger-the-better concept using Equation (2), while delivery and cost are normalized by applying the smaller-the-better concept using Equation (3). Next, the grey relational coefficient is determined to demonstrate the best and actual normalized results. This is done by applying Equation (5), and the outcomes are presented in the same Table 6. The GRG is then calculated using Equation (6). To compute GRG, the weights are taken from Table 5. The output values are presented in Table 6. The pictorial representation of GRG (supplier score) for all suppliers is shown in Figure 2.

FIGURE 2: Grey relational grades (GRG)

Based on GRG, the supplier with the highest GRG (i.e. supplier 1) has been chosen as the best supplier. With this proposed model, both qualitative and quantitative criteria are integrated to select the best supplier.

Sensitivity analysis

The sensitivity of the developed model during the fluctuations in the values of the parameters is also studied. To confirm the uniformity and reliability of the GRA model, this paper performs the sensitivity analysis. This is done by changing the criteria weight, and the influence on the stability of the solution is noted [44]. Figure 3 and Table 7 illustrate the outcome of the sensitivity analysis. From this, it is understood that the developed model is consistent and reliable.

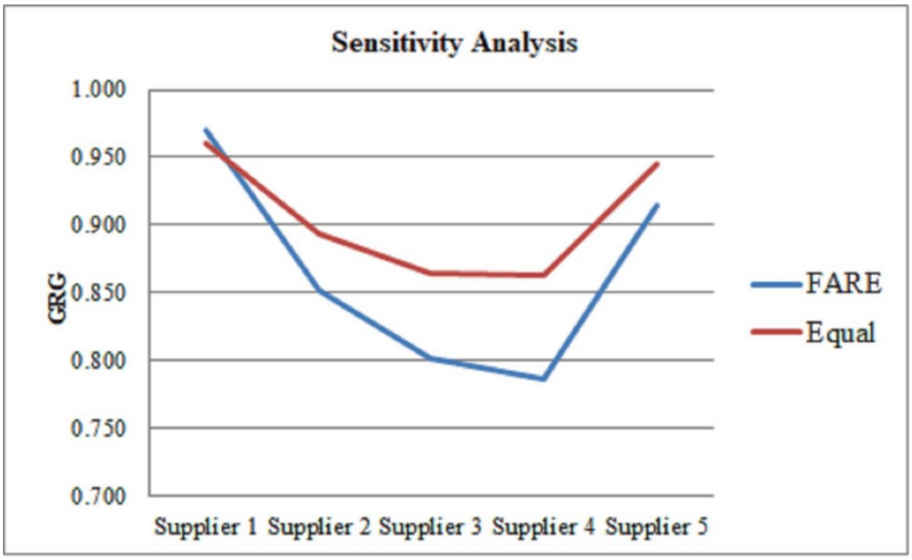

FIGURE 3: Sensitivity analysis

GRG: Grey Relational Grade; FARE: Factor Relationship

Suppliers	GRG	
	Using Weights by FARE	Using Equal Weights
Supplier 1	0.970	0.961
Supplier 2	0.851	0.894
Supplier 3	0.802	0.865
Supplier 4	0.786	0.863
Supplier 5	0.914	0.945

TABLE 7: Sensitivity analysis

GRG: Grey Relational Grade; FARE: Factor Relationship

Mean absolute deviation of ranks

To validate the ranks in this research, a statistical method known as mean absolute deviation (MAD) is used [45]. In decision-making processes, MAD helps in understanding the reliability and variability of different options. It aids in making informed decisions by providing a measure of uncertainty. MAD is determined using Equation (14):

$$\mathrm{MAD} = \frac{\sum |\Gamma_i - \bar{\Gamma}_i|}{n} \quad (14)$$

where $\bar{\Gamma}_i = \frac{\sum_{i=1}^{n} \Gamma_i}{n}$

The MAD of the proposed model was calculated to be 0.06192. Since the MAD is very low, the results exhibit little variability, indicating consistency and predictability in the dataset.

Comparison

The developed model is compared with the other existing models to prove its reliability. The findings of the proposed model are compared with the solution arrived by the hybrid AHP-GRA approach [19] and hybrid FAHP-GRA approach [20].

Figure *4* shows the comparison of the abovementioned approaches with the developed model. From Figure *4*, it is understood that the developed model is reliable since the outcome is same.

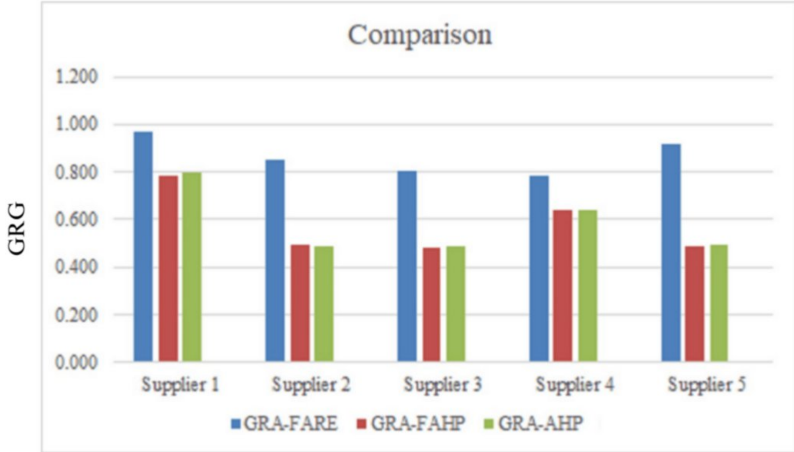

FIGURE 4: Comparison of various models

GRA: Grey Relational Analysis; FARE: Factor Relationship; FAHP: Fuzzy Analytic Hierarchy Process; AHP: Analytic Hierarchy Process; GRG: Grey relational grade

Managerial implications

The proposed hybrid decision-making model has several practical implications for managers and decision-makers in various industries. The integration of GRA and FARE provides a comprehensive framework that can enhance decision-making processes by incorporating both objective data and expert judgment. Managers are often faced with complex decisions where multiple criteria need to be considered simultaneously. By using a hybrid model, managers can ensure that all relevant factors are accounted for in a systematic and balanced manner. The FARE method helps in identifying the relative importance of different criteria, while GRA further refines the decision-making process, ensuring that decisions are based on a more accurate and objective evaluation. The model allows managers to prioritize decision criteria based on expert insights and data-driven methods. In industries such as IT procurement, project selection, or product development, managers often struggle to determine which criteria should be weighted more heavily. By conducting a sensitivity analysis, the model allows managers to assess how changes in criteria weights or expert judgments affect the final decision. This provides decision-makers with an understanding of the robustness and reliability of their choices. The model can be applied to assess and choose between competing options, ensuring that limited resources are invested in the most strategically significant areas. The proposed model is scalable and can be applied to both small-scale decisions and large, complex ones involving multiple stakeholders.

Our findings directly address key challenges in the current supplier selection of that industry. The finding of the study demonstrates an improvement in supplier selection through a scientific approach. This study was conducted in a chemical industry in which the influences of the criteria are not similar to manufacturing sector. The application of our model in selecting suppliers not only improves efficiency but also supports the industry's move toward more sustainable practices.

Conclusions

Today’s business environment is characterized by limited resources, unstable demand, lesser product life cycles, and harder global competition. To survive, organizations need to make accurate decisions while purchasing materials. This paper highlights the significance of the hybrid method that decision-making authorities can apply to make fruitful decisions related to supplier selection. Based on the current study, it was observed that the proposed hybrid technique provides enhanced results for qualitative data and is also more adjustable to fit in with the quantitative and qualitative situation for supplier selection. This developed hybrid model can facilitate to assess and match suppliers on various assessment criteria, which can present a more powerful and reliable technique to select and assess suppliers depending on both quantitative and qualitative criteria. However, the industrial case study is confined to only the process industry, so this model will provide reliable results in the related industries. Our study addresses the needs of supplier selection by providing a structured methodology that can help businesses navigate and adapt to these complex challenges effectively. The model can be expanded to other types of corporate organizations by considering suitable criteria.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Pitchipoo Pandian, Rajakarunakaran Sivaprakasam

Acquisition, analysis, or interpretation of data: Pitchipoo Pandian, Rajakarunakaran Sivaprakasam, Jebakani Devaraj, Krishnaveni Anbazhagan, Jeyakumar Kadarkarai

Drafting of the manuscript: Pitchipoo Pandian, Jeyakumar Kadarkarai

Critical review of the manuscript for important intellectual content: Rajakarunakaran Sivaprakasam, Jebakani Devaraj, Krishnaveni Anbazhagan

Supervision: Rajakarunakaran Sivaprakasam, Jeyakumar Kadarkarai

Disclosures

Human subjects: Consent was obtained or waived by all participants in this study. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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