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Research Article

Evaluating the performance of the raw material providers based on the customer-based LARG (CLARG) paradigm: A machine learning-based method

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Abstract

One of the critically important tasks of supply chain managers is to evaluate the performance of the raw material providers, especially in today's modern and dynamic business environment. In this regard, the current study focuses on the evaluation process of the raw material providers based on some crucial metrics named the customer-based LARG paradigm. For this purpose, based on a real-world case study in the agri-food industry, the main criteria and sub-criteria are determined. Afterward, to evaluate the performance of the potential raw material providers, a machine learning-based method by combining the stochastic best-worst method and weighted decision tree is developed. In general, this research contributes to the literature by proposing an efficient machine learning-based model to investigate the raw material provider selection problem for the agri-food industry based on the customer-based LARG paradigm. The results obtained from the implementation of the developed approach show that the general, leagility, resilience, customer-based, and green criteria are the most significant ones, respectively. Also, among the sub-criteria, "Service level", "Robustness", "Cost", "Quality", "Manufacturing flexibility", "Delivery speed", "Waste management", and "Restorative Capacity" are specified as the best ones. Additionally, based on the obtained results, the effectiveness, reliability, and validity of the proposed machine learning-based approach are confirmed, as the model evaluates the performance of suppliers with an accuracy of approximately 92%.

Keywords: Raw material provider selection, LARG paradigm, Customer-based indicators, Machine learning-based model, Agri-food industry

1. Introduction

The evaluation of Raw Material Providers (RMPs) is a critical aspect of supply chain management (Fallahpour, Nayeri, et al. 2021a; Khameneh et al. 2023). Raw materials are the building blocks of any product, and the quality and consistency of these materials can significantly impact the final product's quality and cost. Therefore, it is essential to evaluate raw material providers to ensure that they meet the required standards and specifications. The evaluation process includes assessing the provider's quality management system, production processes, product testing procedures, and compliance with regulatory requirements (Nayeri, Khoei, et al. 2023). By conducting this evaluation, companies can identify potential risks and take proactive measures to mitigate them. The evaluation of RMPs also helps companies to build strong relationships with their suppliers. When companies work closely with their suppliers, they can collaborate on product development, cost reduction, and quality improvement initiatives. This collaboration can lead to a more efficient supply chain, reduce lead times, and increase overall customer satisfaction. Additionally, by evaluating raw material providers, companies can identify potential areas for improvement and work with their suppliers to implement changes that can benefit both parties. Overall, the evaluation of RMPs is critical for ensuring a reliable supply chain and delivering high-quality products to customers.

In recent years, the tendency of researchers has shifted toward incorporating different crucial aspects into the evaluation process of RMPs. In this regard, LARG paradigm (Lean, Agile, Resilient, and Green) is one of the popular indicators to assess the performance of the RMPs in recent years (Ghazvinian et al. 2024; Sahu et al. 2023). In this regard, the concept of leagility that refers to the combination of leanness and agility concepts is a hybrid supply chain management strategy that combines the principles of both lean and agile methodologies. The term "leagile" itself is a combination of "lean" and "agile." This approach aims to achieve the efficiency and cost reduction benefits of lean manufacturing while also incorporating the flexibility and responsiveness of agile supply chain practices (Rostami et al. 2023). Also, resilience is a concept that focuses on improving the ability of the supply chain to deal with disruptions (Ekinci et al. 2024; Javan-Molaei et al. 2024). Eventually, green concept is a well-known feature that tries to reduce environmental damages of supply chain activities (Agyabeng-Mensah et al. 2024). Based on the literature, considering the LARG paradigm can significantly improve the performance of the supply chain (Anvari 2021; Nayeri et al. 2021; Salleh et al. 2020). Hence, motivated by the mentioned points, this work

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incorporated the mentioned paradigm in the evaluation process of the RMPs.

It is undeniable that one of the most important members of each supply chain is customers. In this regard, considering the customer satisfaction in supply chain management is critically important. In this way, there is a well-known concept in the literature named customer-based indicators. Overall, customer-based indicators are metrics used to measure the performance of a supply chain from the perspective of the end customer (Tavakoli, Tajally, et al. 2023). These indicators are critical for companies to assess how well they are meeting customer needs and expectations, and to identify areas for improvement. Customer-based indicators are essential for companies to monitor and improve their supply chain performance from the perspective of the end customer. By prioritizing customer needs and preferences, companies can build a competitive advantage and drive long-term success (Asadabadi 2017; Tavakoli, Ghanavati-Nejad, et al. 2023). Hence, the current work considers this metric in the evaluation process of the RMPs.

Owing to the critical role of the aforementioned points, the current article focuses on the evaluation process of the RMPs based on the customer-based LARG (CLARG) paradigm. To do this, by considering a real-world case study in the agri-food industry, this research specifies the major indicators based on the experts and literature. In the next step, to assess the performance of the RMPs, the current article presents a hybrid machine learning-based model. In general, the main contribution of the current work is to propose an efficient machine learning-based model to evaluate the performance of the RMPs in the agri-food industry by considering the CLARG paradigm for the first time. The use of hybrid data-driven approaches can evaluate and estimate supplier performance with greater accuracy. Moreover, this research aims to answer the following questions: (i) what are the main indicators for evaluating the RMPs based on the CLARG paradigm? (ii) how can develop an efficient machine learning-based model to assess the RMPs? (iii) which criteria are the most important ones? and (iv) which RMP has the best performance based on the CLARG paradigm?

In this work, Section 2 to reviews the literature. Section 3 provides the case study and indicators. Section 4 presents the methodology. Section 5 focuses on numerical results. Eventually, Section 6 presents the conclusion.

2. Literature Review

2.1. Related works

In this section, a review of the literature on supplier evaluation is conducted. Various studies have been carried out in the field of row material providers, covering different dimensions. For example, (Pamucar et al. 2020) introduced a novel fuzzy-neutrosophic composite decision-making approach for selecting resilient RMPs. They utilized a Dombi aggregator to evaluate the indicators and applied the MABAC (Multi-Attribute Border Approximation Area Comparison) tool to assess the RMPs. This approach is particularly innovative due to its integration of fuzzy and neutrosophic elements. (Fallahpour, Nayeri, et al. 2021b) introduced a hybrid model to assess the RMPs evaluation process within the palm industry, focusing on resilience and sustainability indicators. They conducted their study on a Malaysian company, identifying relevant indicators and alternatives. The next phase involved calculating the weights of these criteria using various decision-making approaches. Finally, the potential RMPs were ranked using the FIS method.

(Shao et al. 2022) investigated and evaluated stable and resilient RMPs in the context of disruptions caused by the Corona epidemic. They developed a multi-objective mathematical model, which was solved using the novel nRa-NSGA-II algorithm. Their proposed model, focused on the supply chain of medical equipment during the Corona era, placed special emphasis on resilience. (Sazvar et al. 2022) proposed a data-driven model for evaluating and selecting RMPs, focusing on sustainability and resilience. Their study identified 22 criteria and employed the FBWM method to determine the weights of these indicators. FIS was used to establish rules for assessing supplier performance, and machine learning algorithms were utilized to build the evaluation model. The findings indicated that managers prioritized responsiveness and capability. This model can be adopted by other enterprises for supplier selection by leveraging historical data. (Hosseini et al. 2022) carried out a study focused on selecting stable suppliers and allocating orders under conditions of uncertainty. Initially, they identified evaluation criteria based on sustainability and resilience paradigms and used the best-worst method to determine the weights of these indicators. Subsequently, they employed a mathematical allocation model to determine the order quantities for each supplier.

(Tavakoli, Tajally, et al. 2023) examined the process of customer-based evaluation for an online retailer, emphasizing resilience and sustainability indicators. They began by applying the FBWM method to assign weights to crucial indicators for supplier evaluation. Following this, they employed the Markov approach to analyze behavioral changes. Finally, they utilized the QFD method to prioritize and assign weights to the suppliers. (Rostami et al. 2023) carried out a study aimed at evaluating medical equipment suppliers based on sustainability principles within supply chains. They combined multi-criteria decision-making with goal programming to achieve their research objectives. The results revealed that production scheduling, agility, stability, and flexibility were the most critical criteria in the supplier selection process, each having similar weights. In contrast, digitalization indicators were deemed the least influential. The authors then calculated the RMPs' weights using the TOPSIS and VIKOR methods, which allowed them to prioritize and compare the suppliers. (ForouzeshNejad 2023) focused on the RMPs selection problem for a medical equipment firm during the Corona pandemic, adopting paradigms such as Lean, Agile, Sustainability, and Industry 4. He assigned weights to the identified criteria using the rough best-worst method (RBWM). Following this, the prospective suppliers were ranked based on their performance across

all criteria using the multi-attributive border approximation area comparison (IR-MABAC) method.
(Nayeri, Khoei, et al. 2023) proposed a data-driven model for evaluating suppliers and allocating orders to them based on resilience and sustainability criteria. In their study, a novel approach based on BWM was developed to assess suppliers, and then a data-driven approach was used to address uncertainty, leading to the solution of the supply chain network model. Their findings indicate that data-driven models perform better than heuristic methods. (Liang et al. 2024) devised an innovative decision-making approach to address the issue of digital RMP selection by leveraging blockchain technology. They introduced a robustness PROMETHEE method and incorporated learning interactive criteria in their analysis. (Siddiquee et al. 2024) introduced a framework for selecting sustainable RMPs for pharmaceutical companies in emerging economies. Their study revealed that public engagement and economic factors hold greater significance than environmental components in these regions. (Sheykhzadeh et al. 2024) addressed supplier evaluation in the pharmaceutical industry by focusing on green, resilient, and agile characteristics. They began by identifying essential indicators and potential alternatives. The team then developed a hybrid approach that combines the fuzzy Best Worst Method (BWM) with the additive ratio assessment technique, enabling the determination of indicator weights and the assessment of suppliers.
The summary of the literature review is presented in Table 1.

Table 1
The summary of articles reviewed

Paper	Customer-based	LARG				Case study	Methodology
		Lean	Agile	Resilience	Green		
(Pamucar et al. 2020)				×		---	Fuzzy-neutrosophic MABAC
(Fallahpour, Nayeri, et al. 2021b)				×	×	Palm industry	FDEMATEL, FBWM, FANP, FIS
(Shao et al. 2022)				×	×	Medical Equipment	Mathematical model - novel nRa-NSGA-II
(Sazvar et al. 2022)				×	×	Medicine	FBWM-FIS-ML
(Hosseini et al. 2022)				×	×	---	BWM - Mathematical model
(Tavakoli et al. 2023)	×			×		Online retailer	FBWM, Markov, QFD
(Rostami et al. 2023)		×	×	×		Healthcare system	Goal Programming based on BWM
(ForouzeshNejad 2023)		×	×		×	Healthcare system	RBWM - IR-MABAC
(Nayeri, Khoei, et al. 2023)				×	×	Healthcare system	FSBWM – DDFRS
(Liang et al. 2024)			×			Pork	Robustness PROMETHEE
(Siddiquee et al. 2024)					×	Pharmaceutical	TOPSIS - COA
(Sheykhzadeh et al. 2024)				×		Pharmaceutical	BWM – ARAS
This work	✓	✓	✓	✓	✓	Wheat flour	Stochastic BWM – Weighted Decision Tree

2.2. Research gaps and contributions

As observed in the reviewed literature and Table 1, despite valuable studies conducted in the field of RMP evaluation, research gaps still exist in this area. One of the fundamental gaps in contemporary studies is the lack of attention to customer perspectives and their indicators in evaluating the performance of various parts of the supply chain. The customer, who typically receives services at the end of the supply chain, perceives the performance effects of all supply chain components. Therefore, considering customer-centric criteria is highly significant in the evaluation of suppliers and RMPs. In this context, this study incorporates customer-centric indicators into the LARG paradigm to provide a more comprehensive evaluation. Moreover, due to the large volume of data generated in today's world, the use of data-driven models has expanded. Consequently, this study develops a hybrid machine learning algorithm based on the resulting model to evaluate the performance of RMPs in real-time and provide an analysis. Thus, this study addresses the mentioned research gaps through the following innovations:

- This is the first study that considers the customer-based criteria alongside LARG paradigm in evaluating RMP performance.
- The present work develops a hybrid data-driven model based on input weights derived from expert opinions.
- This research proposes a machine learning-based model to evaluate RMP performance;
- This article focuses on a real-world case study in the wheat flour industry.

3. Case Study and Indicators

The case study of this article focuses on wheat flour RMPs. Some of these RMPs also manage wheat farms and handle both the harvesting and production of flour. In other cases, the RMPs purchase wheat and only carry out the production of wheat flour. For the organization under study, which has a monthly wheat flour supply order, it must choose among 7 material providers. Accordingly, evaluations are conducted monthly, assessing RMPs based on various indicators. It is important to note that flexibility in evaluating RMPs is crucial for the organization, enabling it to effectively carry out these operations on a monthly basis. Therefore, comprehensive indicators and a flexible approach are required to evaluate the performance of RMPs with suitable speed and accuracy.

Evaluating RMPs in the wheat industry is of paramount importance due to the critical role these providers play in ensuring a stable and high-quality supply of wheat flour, a staple product in many markets. The industry is inherently susceptible to various disruptions, such as fluctuations in wheat supply, environmental challenges, and market volatility. Therefore, it is essential to assess RMPs not only on traditional metrics like cost and quality but also on comprehensive indicators that include resilience, agility, green, and customer satisfaction. These factors are crucial for maintaining a robust and responsive supply chain that can adapt to changing conditions and meet the ongoing demands of the market. Incorporating such multifaceted criteria into the evaluation process allows organizations to make more informed decisions, ensuring that they partner with suppliers who can consistently deliver under diverse circumstances, thereby safeguarding the overall efficiency and stability of the supply chain.

In the following, we present the considered indicators. In this regard, it should be noted that the potential indicators first extracted from the relevant literature (for example see (Abbasi 2023; Alamroshan et al. 2022; Fallahpour, Nayeri, et al. 2021a; Fallahpour, Wong, et al. 2021; ForouzeshNejad 2023; Li et al. 2020; Nayeri, Khoei, et al. 2023; Rostami et al. 2023; Zekhnini et al. 2023)). Then, the experts selected the most related ones for this research. Figure 1 depicts the considered indicators.

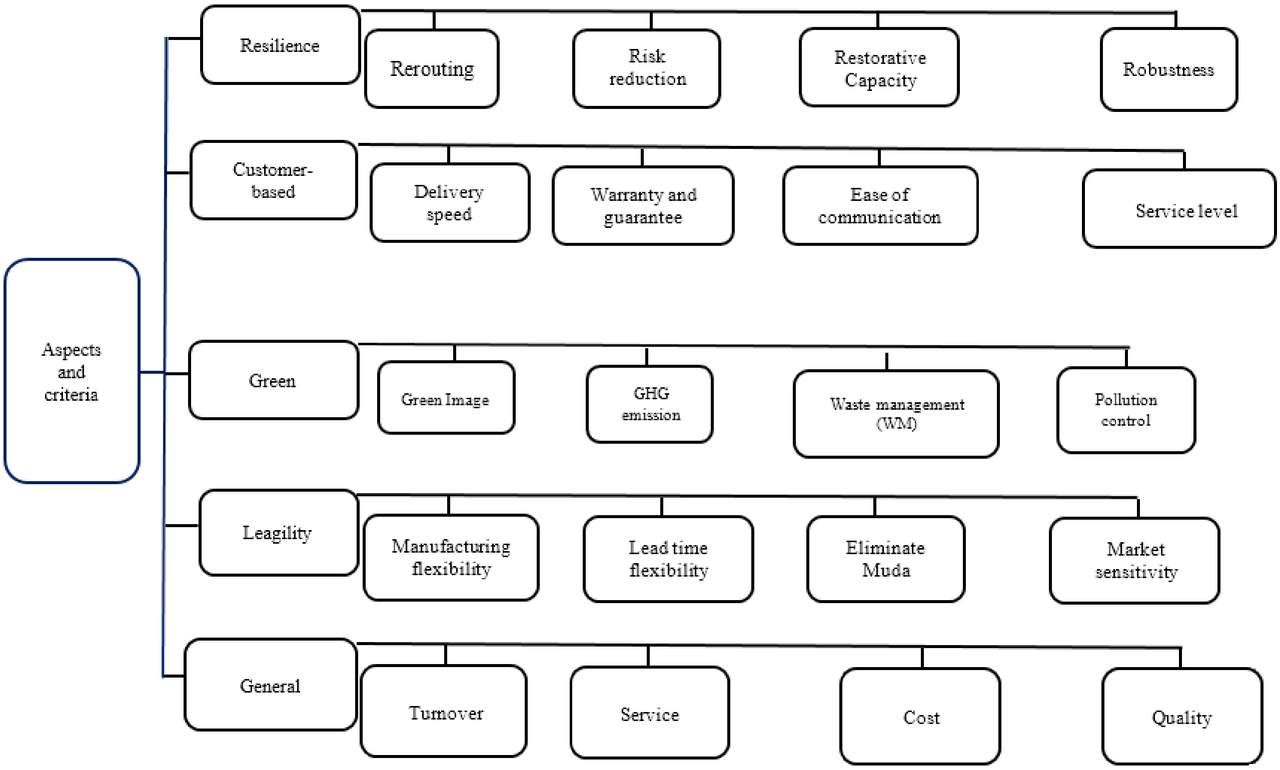

Fig. 1. The determined indicators

4. Methodology

In this section, the methodology of the problem is explained. In this study, scenario-based approaches were used to assign weights to the RMP evaluation criteria, allowing for the assessment of indicator weights considering different scenarios and conditions. Following this, a weighted decision tree algorithm was employed to develop the data-driven model for evaluating RMPs. The input feature weights for this algorithm were calculated using the scenario-based Stochastic BWM method, which takes into account expert opinions and various scenarios to more accurately estimate the algorithm's performance. Overall, the SBWM method was used for weighting the evaluation criteria, and the WDT was utilized for developing the data-driven model for evaluating RMPs. This approach incorporates both expert opinions in the evaluation process and leverages data-driven methods and documented data.

4.1. Stochastic BWM

One of the popular decision-making techniques that widely used in recent years is the Best-Worst Method (BWM) presented by (Rezaei 2015). This method has several significant benefits compared to the similar methods like AHP such as increasing the reliability and decreasing the computational burden (Aria et al. 2020). Besides its merits, the BWM could not deal with the uncertain environment of the decision-making problems. Hence, in recent years, researchers developed different versions of the BWM to tackle uncertainty (e.g., fuzzy BWM and grey BWM). One of the recently-introduced efficient variants of the BWM is the Stochastic BWM proposed by (Nayeri, Sazvar, et al. 2023). This approach defines several scenarios and compare the indicators under these scenarios. It should be noted that the main reasons for focusing of the scenario-based programming is that according to the literature this type of uncertainty plays an important and crucial role in the decision-making problems (Abdo and Flaus 2016; Foley et al. 1997; Nayeri, Sazvar, et al. 2023). Here, this method has been defined briefly. To implement the stochastic BWM, at the outset, the considered scenarios should be defined. Then, the best and worst indicators must be determined by decision-makers. In the next step, the comparison vectors should be formed using numbers 1-9. Then, the weights of the indicators are calculated using Model (1). In this model, P_s denotes the probability of scenario s, a_{jWs} is the score of the j-th indicator over the worst indicator under scenario s, a_{Bjs} is the score of the best indicator over the j-th indicator under scenario s, ws_{js} demonstrates the weight of the j-th indicator under scenario s, w_j is the final weight of the j-th indicator, and ξ_s denotes the consistency ration (CR) under scenario s

$$
\begin{aligned}
& Min \sum_s P_s.\xi_s && \\
& \left|ws_{Bs} - a_{Bjs}.ws_{js}\right| \leq \xi_s && \forall j,s \\
& \left|ws_{js} - a_{jWs}.ws_{Ws}\right| \leq \xi_s && \forall j,s \\
& \sum_j ws_{js} = 1 && \forall s \\
& w_j = \sum_s P_s.ws_{js} && \forall j \\
& ws_{js}, w_j \geq 0 && \forall j,s
\end{aligned}
\tag{1}
$$

4.2. Weighted Decision Tree (WDT)

The decision tree is one of the popular and interpretable algorithms in machine learning for classification. A decision tree has a tree-like structure where internal nodes represent attributes, branches represent attribute values, and leaves represent class labels or output values (Moshkov 2021; Wang et al. 2018). In the developed algorithm of this paper, feature weights are applied as the main components for building the decision tree using the SBWM method, aiming to develop a more accurate model based on expert opinions. The use of this method enables real-time evaluation of RMPs without the need for pairwise comparisons of options. This approach increases the agility and flexibility of RMP performance evaluation. In this context, the steps of the desired decision tree algorithm, modeled after the conventional decision tree algorithm, include the following stages (Liu et al. 2022):

Step 1 (Start with the initial dataset):

- Data X consists of m samples and n features along with labels y.
- Feature weights w = [w_1, w_2, ..., w_n] are pre-calculated and provided to the algorithm.

Step 2 (Select the optimal feature with weighting):

- For each feature i and each possible threshold value t (such as unique values of the feature), a splitting criterion like Gini Impurity or Information Gain is calculated and combined with the feature weights:

$$\text{Weighted Criterion}_{i,t} = \text{Criterion}_{i,t} \times \text{W}_i$$

- The feature and threshold with the highest Weighted Criterion are selected as the best split.

Step 3 (Split the data):

- The data is split into two groups based on the selected best feature and threshold: data with values less than the threshold and data with values greater than or equal to the threshold.

Step 4 (Create an internal node or leaf):

- If all data samples in a node belong to a single class or other stopping conditions like reaching the maximum depth or a minimum number of samples in a node are met, the node is considered a leaf and is assigned the majority class.
- Otherwise, a new internal node is created, and the process is repeated for each group.

Step 5 (Repeat the process for child nodes):

- For each child node, steps 2 to 4 are recursively repeated until the stopping conditions are met.

Overall, this developed algorithm, due to the inclusion of feature weights, will provide greater accuracy in the agri-food industry and organizations, and thus it has been developed for this purpose.

5. Computational Results

5.1. Measuring the importance of criteria

This section is dedicated to computing the weights of the indicators. In this regard, first of all, the comparison vectors are formed based on the experts. Inspired by the literature, in this work, we consider three scenarios as follows: (S1: pessimistic scenario, $PS_{s1} = 0.25$; S2: most likely scenario, $PS_{s2} = 0.50$; and S3: optimistic scenario, $PS_{s3} = 0.25$) A sample of the relevant questionnaire is provided in the Appendix. After implementing the stochastic BWM, the obtained results are shown in Table 2. Based on this table, among the criteria, general, leagility, resilience, customer-based, and green respectively are measured as the most important ones. Also, among the sub-criteria, “Service level”, “Robustness”, “Cost”, “Quality”, “Manufacturing flexibility”, “Delivery speed”, “Waste management”, and “Restorative Capacity” are specified as the most desirable ones.

Table 2
The weights of the indicators

Criteria	Criteria's weight	Sub-criteria	Sub-criteria's initial weight	Sub-criteria's final weight
Resilience	0.2013	Rerouting	0.2373	0.04777
		Risk reduction	0.2515	0.05063
		Restorative Capacity	0.2536	0.05105
		Robustness	0.2576	0.05185
Customer-based	0.1994	Delivery speed	0.2585	0.05154
		Warranty and guarantee	0.2455	0.04895
		Ease of communication	0.2357	0.04700
		Service level	0.2603	0.05190
Green	0.1965	Green Image	0.2385	0.04687
		GHG emission	0.2579	0.05068
		Waste management	0.26	0.05109
		Pollution control	0.2436	0.04787
Leagility	0.2013	Manufacturing flexibility	0.2571	0.05175
		Lead time flexibility	0.2536	0.05105
		Eliminate Muda	0.2486	0.05004
		Market sensitivity	0.2407	0.04845
General	0.2015	Turnover	0.2362	0.04759
		Service	0.25	0.05038
		Cost	0.2569	0.05177
		Quality	0.2569	0.05177

5.2. Assessing the performance of RMPs

In this section, the performance of RMPs is evaluated and analyzed. To this end, a model based on WDT has been developed, where the input weights of the evaluation indicators are calculated using the SBWM method. One of the initial steps in developing data-driven models is analyzing the relationship between the features of the model, which in this study are the RMP evaluation indicators. Figure 2 shows the heatmap of the correlation coefficients between the indicators. For example, it is observed that cost has a direct and strong relationship with quality, meaning that as quality increases, the cost also increases. On the other hand, market sensitivity has a direct and strong relationship with service. Generally, the closer the correlation coefficient is to 1, the stronger and more direct the relationship. Conversely, the closer it is to -1, the stronger the inverse relationship. A value close to zero indicates no relationship.

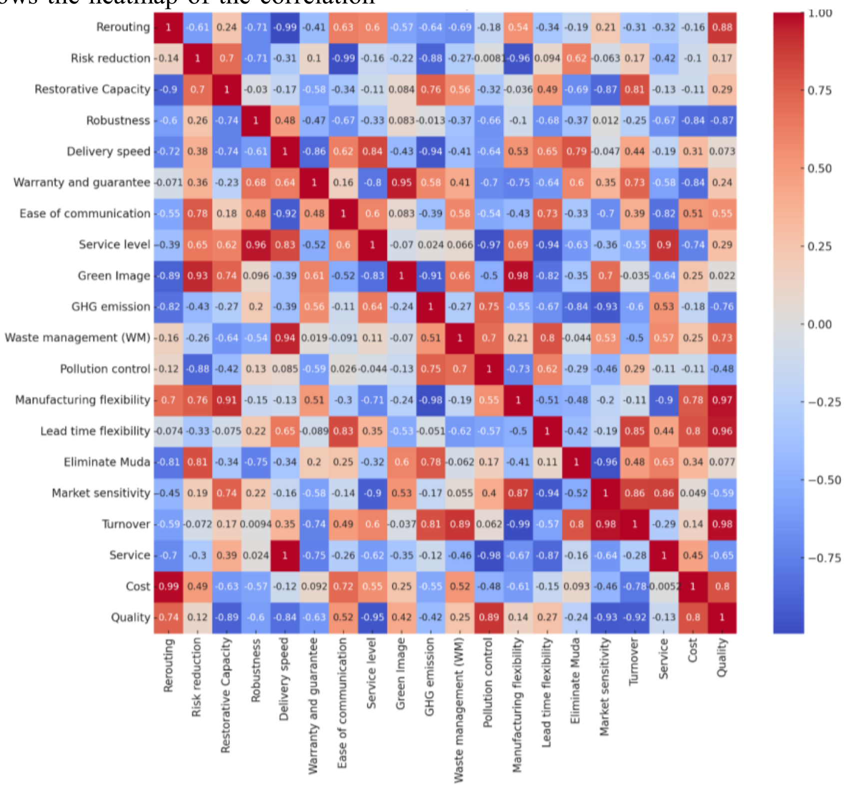

Fig. 2. Heat map diagram of correlation coefficient between indicators

For the development of the model, a total of 960 data records were collected, with 80% allocated for training data and 20% for testing data. All 960 data records were clean and used in the model development. The dataset is structured such that each record contains a value for each of the evaluation indicators and a performance label. The labels include "selected," "saved," and "rejected."

Figure 3 illustrates a portion of the decision tree from this study based on 100 data records, which determines the data labels. For example, if Eliminate Muda <= 0.043, the RMP is rejected. However, if this condition is not met and green image > 0.89 and lead time flexibility > 0.598, then the RMP is approved. Using this tree, one can effectively evaluate an RMP individually and at any given time interval.

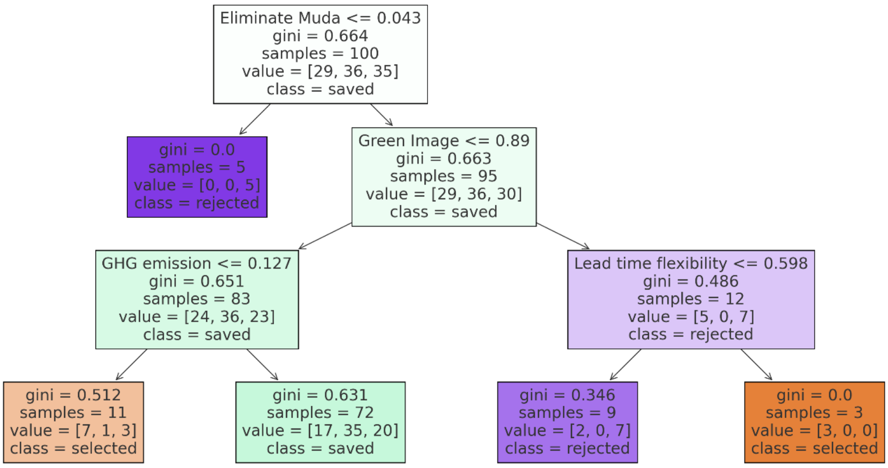

Fig. 3. Part of the decision tree diagram of this article

Now, according to the developed model, the RMPs in this study, which include 7 cases, have been evaluated in Table 3. It can be observed that two RMPs have been selected, two have been saved, and three have been rejected.

Table 3
Performance evaluation of potential RMPs

Raw Material Provider	Label
RMP 01	Rejected
RMP 02	Selected
RMP 03	Saved
RMP 04	Saved
RMP 05	Selected
RMP 06	Rejected
RMP 07	Rejected

5.3. Performance of the stochastic BWM

5.3.1. Comparing with other methods

To examine the performance of the employed stochastic BWM, in this section, we compare its outputs with other methods (fuzzy AHP and fuzzy BWM). In this regard, Figure 4 shows a comparison among these methods. Based on this figure, many of the achieved weights are close to each other that confirms the validity and effectiveness of the employed method.

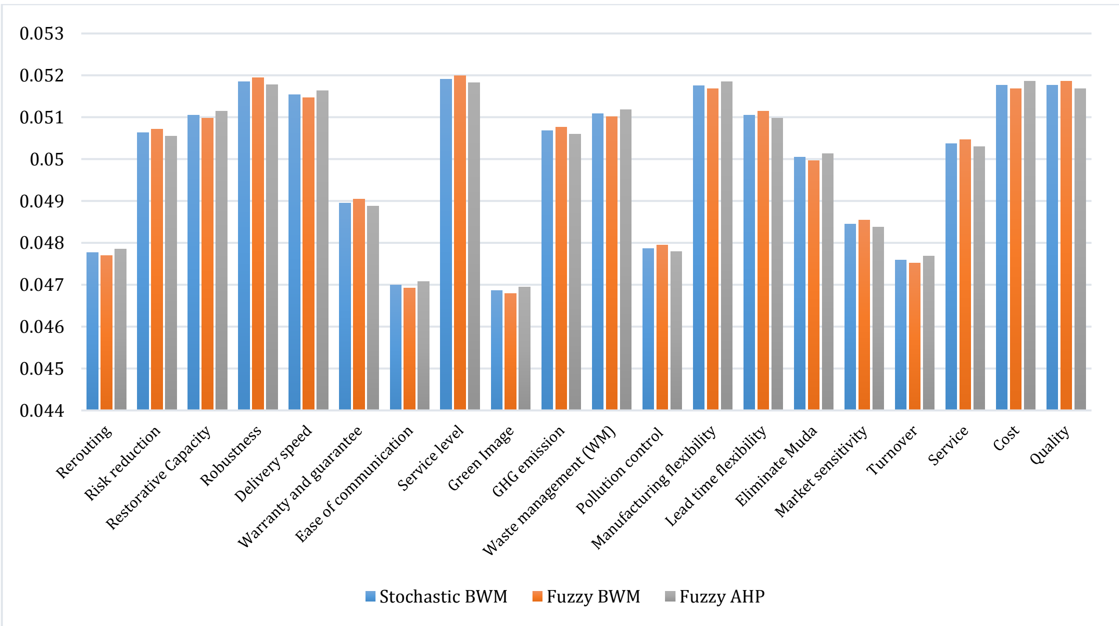

Fig. 4. Comparing the weights of the indicators achieved by different methods

5.3.2. Checking the CR

In this section, to assess the reliability and efficiency of the applied approach, we check the obtained consistency ratios. In this regard, Figure 5 demonstrates the CRs calculated by each method in different steps. As shown in this figure, in all steps, the employed stochastic BWM shows better performance in the term of the CR metric, which confirms its reliability and efficiency.

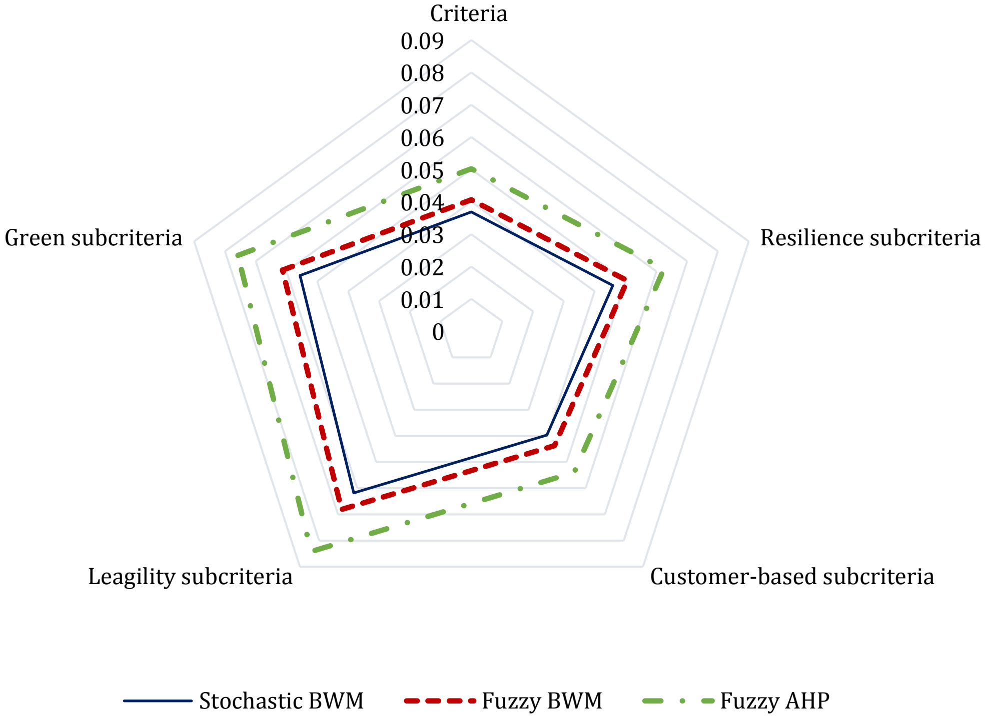

Fig. 5. Comparing the CRs achieved by different methods

5.4. Performance of the WDT

To evaluate the accuracy and performance of the developed WDT algorithm, we use the indicators of accuracy, precision, recall, and F1-score. These metrics are calculated based on equations 2-5.

$$Accuracy = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FP_i} \quad (2)$$

$$Precision = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FN_i} \quad (3)$$

$$Recall = \frac{\sum_{i=1}^{l} TP_i}{\sum_{i=1}^{l} TP_i + FP_i} \quad (4)$$

$$F1 - score = \frac{2 * (precision * recall)}{(precision + recall)} \quad (5)$$

Where:

True Positive (TP_i): Occurs when the data genuinely has a P_i label and the predicted value matches it.

False Positive (FP_i): Occurs when the data does not have a P_i label, but the prediction result incorrectly indicates it.

To accurately assess the performance and make a proper comparison of the developed WDT algorithm, it is compared with the Decision Tree (DT), Support Vector Machine (SVM), and Artificial Neural Network (ANN) algorithms using the dataset from this study. Table 4 shows the comparison of performance indicators for these algorithms, demonstrating that the developed WDT algorithm has the best performance.

Table 4
Comparison of the performance of the WDT algorithm with other algorithms

Algorithm	Accuracy	Recall	Prec.	F1-score
WDT	0.913	0.923	0.918	0.915
DT	0.886	0.891	0.879	0.888
SVM	0.746	0.749	0.786	0.755
ANN	0.855	0.843	0.841	0.823

5.6. Findings and discussions

Given the critical role of the RMP selection problem in supply chain management, this work has addressed the evaluation process of the RMPs by considering some crucial dimensions namely the CLARG paradigm. In this regard, the current article developed a machine learning-based approach to assess the RMPs' performance in the agri-food industry. For this purpose, first of all, the main criteria and sub-criteria were identified based on the literature and experts. In this regard, we proposed five criteria including the resilience, customer-based, leagility, general, and green dimensions. It should be noted that we consider four sub-criteria for each of the considered criteria. To measure the weights of the indicators, one of the recently introduced methods called the stochastic BWM is employed. According to the outputs of this method, the general, leagility, and resilience criteria have been specified as the best ones. Also, the achieved outputs demonstrated that the "Service level", "Robustness", "Cost", "Quality", "Manufacturing flexibility", "Delivery speed", "Waste management", and "Restorative Capacity" have been measured as the most desirable sub-criteria. On the other hand, the results of comparing the outputs of the stochastic BWM with other well-known methods confirmed its effectiveness and validity. Moreover, based on the achieved results, the performance of the applied stochastic BWM outperforms other approaches in the term of the CR metric, which demonstrated its efficiency and reliability. On the other hand, a weighted decision tree algorithm was developed to evaluate the performance of RMPs using data and flexibly assess them at any given time interval. This algorithm estimates the performance of RMPs with an accuracy of over 91%. Using the developed model, the performance of the seven RMPs studied was also evaluated, resulting in two being selected, two being saved, and three being rejected.

5.7. Managerial insights

The main objective of this study is to develop a hybrid data-driven model for evaluating the performance of RMPs in the food industry, specifically wheat flour. In this context, evaluation indicators for RMPs were identified in the categories of customer-based, lean, agile, resilient, and green, ensuring comprehensive performance assessment. Therefore, it is recommended that managers in the food industry not rely solely on traditional indicators for evaluating suppliers and RMPs but also consider resilience, agility, and customer-centric indicators due to the importance of competitiveness in today's world. The findings of this research demonstrate that using these indicators together provides significant benefits in performance evaluation.

Furthermore, due to the large volume of data generated in recent years within organizations and supply chains, it is suggested that managers utilize data-driven hybrid approaches and models for evaluating the performance of organizational units. Intuitive approaches do not have sufficient validity, and purely data-driven approaches may be prone to errors due to uncertainties and inaccuracies in organizational data. Therefore, it is recommended to use hybrid approaches that leverage both existing data and expert opinions in critical modeling aspects. The findings of this study also show that hybrid approaches perform better than purely data-driven methods. Thus, managers are always advised to develop performance evaluation models using hybrid methods.

5.8. Theoretical implications

This study makes several significant theoretical contributions to the field of supply chain management, particularly in the context of evaluating raw material providers (RMPs). First and foremost, the research introduces an innovative approach by integrating customer-based criteria with the established LARG (leanness, agility, resilience, and green) paradigm. This is a novel contribution as previous studies primarily focused on internal and operational criteria without fully considering the customer's perspective. By doing so, the study broadens the theoretical understanding of supplier evaluation, highlighting the importance of aligning RMP performance metrics with customer expectations, which is crucial in today's customer-centric market.

Secondly, the study advances the application of machine learning in supply chain management by developing a hybrid data-driven model that combines the stochastic best-worst method (BWM) with a weighted decision tree algorithm. This methodological innovation contributes to the literature by demonstrating how expert opinions can be systematically integrated into a machine learning framework to enhance the accuracy and reliability of supplier evaluations. The model's high accuracy (approximately 92%) in assessing supplier performance provides empirical evidence of the effectiveness of this hybrid approach, offering a new direction for future research on data-driven decision-making in supply chains.

Moreover, the focus on a real-world case study in the wheat flour industry adds practical relevance to the theoretical contributions, bridging the gap between theory and practice. By applying the proposed model in a complex, real-world scenario, the study not only validates the model's robustness but also provides a template for future research in other sectors. This practical application reinforces the theoretical proposition that integrating customer-based criteria with traditional supply chain paradigms can significantly improve the assessment and selection of RMPs.

Overall, this study enriches the theoretical discourse on supply chain management by introducing a customer-centric, data-driven approach to RMP evaluation, and it lays the groundwork for future research to explore similar integrations in different industries and contexts.

6. Conclusions and outlook

6.1. Concluding remarks

RMP selection is crucial for the success of a business due to several reasons. Firstly, it directly impacts the quality and reliability of the products or materials sourced, influencing customer satisfaction and brand reputation. Additionally, selecting the right RMPS can lead to cost savings, improved supply chain resilience, and access to innovation and expertise. Therefore, this work focused on the evaluation process of the RMPs based on the customer-based LARG (CLARG) paradigm. To this end, a machine learning-based model was developed by combining the stochastic BWM and WDT method. Overall, the main contribution of the present article is to develop a machine learning-based model to investigate the RMP selection problem for the agri-food industry based on the CLARG paradigm for the first time. According to the achieved results, among the criteria, general, leagility, resilience, customer-based, and green respectively are measured as the most desirable ones. Also, among the sub-criteria, “Service level”, “Robustness”, “Cost”, “Quality”, “Manufacturing flexibility”, “Delivery speed”, “Waste management”, and “Restorative Capacity” are specified as the best ones. Also, using the developed hybrid data-driven algorithm (WDT), the performance of potential RMPs was examined and evaluated. The findings showed that RMPs 02 and 05 were selected, RMPs 03 and 04 were saved, and RMPs 01, 06, and 07 were rejected. Moreover, the obtained outputs demonstrated the efficiency, validity, and reliability of the proposed machine learning-based model.

6.2. Research limitations and future directions

This section is dedicated to presenting the research limitations and also providing some suggestions for future studies. In this regard, one of the main limitations of this work is to focus on the only stochastic uncertain environment. In this way, future researchers can investigate the research problem under other uncertain environments (like grey, fuzzy-scenario, etc.). Also, another limitation of this research is to ignore some crucial indicators. For example, future papers can consider the digitalization and globalization indicators to evaluate the performance of the RMPs. Also, this work considered only three scenarios to implement the stochastic BWM. In this regard, future papers can consider more scenarios to bring the problem closer to real-world conditions. Additionally, developing this model using other machine learning algorithms and comparing the findings with those of this study is another suggestion that researchers can explore. Furthermore, the model's applicability for evaluating RMPs in various industries also presents a viable area for future research.

Appendix

Table A.1
A sample of questionnaire to form the comparison vector between the best indicator and other ones

Expert	**Indicators**	**Criterion #1**			**Criterion #2**			**Criterion #3**			**Criterion #4**		
	Scenario	1	2	3	1	2	3	1	2	3	1	2	3
1	**The best indicator**												
2													
3													
Average													

Table A.2
A sample of questionnaire to form the comparison vector between the worst indicator and other ones

		The worst indicator			
		Expert			
Indicators	**Scenario**	**1**	**2**	**3**	**Average**
Criterion #1	1				
	2				
	3				
Criterion #2	1				
	2				
	3				
Criterion #3	1				
	2				
	3				
Criterion #4	1				
	2				
	3				

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