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Research Article

Development of a data-driven decision-making model for evaluating agile and resilient suppliers in the context of the circular economy (Case study: Automotive industry)

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Abstract

This study focuses on developing a data-driven model for evaluating and selecting suppliers in the automotive industry, emphasizing agility, resilience, and circular economy principles. Through an extensive literature review, 14 evaluation criteria were identified, which were subsequently weighted using expert survey data and the Fuzzy Best-Worst Method (FBWM). The analysis revealed that resilience is the most crucial dimension in supplier evaluation, with excess inventory and backup suppliers ranking as the most significant criteria. Building on these insights, a hybrid Weighted Support Vector Machine (WSVM) algorithm was employed to assess supplier performance, integrating feature weights derived from the FBWM. The developed model demonstrated over 90% accuracy in predicting supplier performance, showcasing its robustness and applicability. The findings highlight the importance of resilience in managing supply chain disruptions and underline the critical role of data-driven methodologies in enhancing decision-making processes. Additionally, this research offers practical recommendations for adopting data-driven models in supply chain management, particularly in contexts requiring agility and sustainability. By bridging theoretical frameworks with practical applications, the study provides valuable insights for industry practitioners aiming to optimize supplier selection and improve supply chain efficiency. The proposed approach paves the way for more resilient, sustainable, and adaptive supply chains in the automotive sector and beyond.

Keywords:
Supplier evaluation;
Resilience;
Agility;
Data-driven model;
Circular economy;
Fuzzy Best-Worst Method (FBWM).

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1. Introduction

In today's competitive and globalized world, supplier evaluation is considered one of the key responsibilities of supply chain managers (Lee and Moon 2024; Rostami et al. 2023). Suppliers play a critical role in the supply chain as the quality, cost, and timeliness of raw materials or services they provide directly impact the overall performance of the supply chain (Gidiagba et al. 2023). Selecting the right suppliers can enhance the productivity, flexibility, and competitiveness of the supply chain, leading to reduced costs and improved customer satisfaction. Conversely, weak suppliers may cause issues such as delays, reduced quality, and increased operational costs (Tavakoli, Tajally, et al. 2023; Tavakoli, Torabi, et al. 2023). Therefore, choosing an optimal supplier holds significant importance for organizations.

One of the critical components of modern supply chains is agility. In this context, agility plays a key role in addressing the dynamic changes in the market (Sahu et al. 2023). Agility generally refers to adopting appropriate strategies to enhance a system's ability to cope with business environment fluctuations (ForouzeshNejad 2023). According to studies, considering agility in the supplier evaluation process can significantly improve system performance (Sazvar et al. 2022; Sonar et al. 2022). Hence, incorporating agility as a factor in supplier evaluation is essential for managers to consider. However, given the fundamental challenges in various supply chain contexts, the concept of resilience has also gained greater importance.

Resilience in the supply chain refers to the system's ability to handle disruptions, shocks, and unexpected changes. It is a critical concept for ensuring operational stability in dynamic and uncertain environments (Javan-Molaei et al. 2024). Disruptions such as natural disasters, market fluctuations, raw material shortages, and unexpected events like pandemics can affect the supply chain (Mohammed et al. 2023; Rostami et al. 2023). Resilience allows the supply chain to recover quickly and efficiently to normal conditions, mitigating potential adverse effects (Nayeri et al. 2023; Nessari et al. 2024). Therefore, including resilience indicators in supplier evaluation is another important consideration for managers.

In addition to agility and resilience, environmental concerns have significantly increased in recent years (Nayeri et al. 2023). As a result, managers and researchers have focused on reducing the environmental impacts of supply chain activities. A key concept in this regard is the circular economy. The circular economy offers a framework for consumption and production, including practices such as renting, sharing, repairing, reusing, recycling, and refurbishing existing products and materials to extend their lifecycle (Kusi-Sarpong et al. 2023; Ng et al. 2024). This framework provides a systematic solution to global issues such as climate change, biodiversity loss, waste production, and pollution (Alavi et al. 2021). Given its substantial positive impact on cost reduction and environmental sustainability, incorporating the circular economy into the supplier evaluation process can significantly improve supply chain efficiency. The circular economy affects suppliers by emphasizing the recyclability and reusability of their products (Echefaj et al. 2023). This consideration is particularly critical for manufacturing supply chains, such as the automotive industry.

The automotive industry, as one of the key sectors with significant influence on economic and social development, holds special importance. In this industry, suppliers play a vital role, and traditional methods for evaluating them are no longer sufficient. Considering the complexities involved in component procurement and the associated cost and implementation challenges, adopting hybrid structures that consider multiple criteria is essential.

Given these considerations, the present study focuses on the issue of supplier evaluation in the automotive industry. Some suppliers source components domestically, while others procure them internationally. Therefore, a structure that can comprehensively evaluate suppliers based on available and real-world data is crucial. In this regard, the study adopts data-driven approaches to supplier evaluation, utilizing machine learning algorithms to assess and monitor suppliers.

2. Literature Review

This section provides a review of the literature and articles in the field of supplier evaluation. For example,

(Li et al. 2020) evaluated and selected suppliers by considering lean and agile criteria. In their study, they assessed a textile company in China, initially selecting evaluation indicators and then comparing the criteria to ultimately choose the most suitable option among potential suppliers. (Tavana et al. 2021) also focused on evaluating and selecting digital suppliers. They identified 12 digital criteria for supplier evaluation and assigned weights to them using the fuzzy best-worst method (FBWM). Subsequently, they assessed the suppliers through integrated fuzzy multi-objective optimization (MULTIMOORA) and complex fuzzy relative evaluation of options (COPRAS).

(Hosseini et al. 2022) conducted a study aimed at selecting a sustainable supplier and order allocation under uncertainty. They first identified evaluation criteria based on sustainability and resilience paradigms and extracted the weights of the indicators using the best-worst method (BWM). Then, using a mathematical allocation model, they determined the order quantity for each supplier. (Coşkun et al. 2022) introduced a decision support framework for evaluating and selecting suppliers in the chemical manufacturing industries, grounded in the sustainability paradigm. They initially established various criteria and assigned weights to them using the analytic network process (ANP). Subsequently, by employing the PROMETHEE method, they prioritized 69 desired suppliers. The results indicated that the most significant indicators include reducing pollution levels, minimizing costs, and improving quality.

(Shao et al. 2022) examined and evaluated sustainable and resilient suppliers, considering disruptions related to the COVID-19 pandemic. In their study, a mathematical model was developed to optimize the medical equipment supply chain during the pandemic. Similarly, (Sazvar et al. 2022) proposed a data-driven model for evaluating and selecting suppliers. Their study incorporated resilience and sustainability criteria, with the criteria weights determined using the Fuzzy Best-Worst Method (FBWM). Subsequently, a model was developed using a Fuzzy Inference System (FIS) and machine learning algorithms to assess suppliers. In another study, (Tavakoli, Tajally, et al. 2023) focused on evaluating suppliers for online retailers. Their study also considered resilience, sustainability, and customer-centric criteria. The criteria weights were calculated using FBWM, and suppliers were prioritized using a Markov Chain approach and the QFD method. (Nayeri et al. 2023) evaluated suppliers and allocated orders to them using data-driven approaches. In their study, they considered sustainability and resilience criteria for evaluation and applied an extended method based on BWM to weigh the indicators and assess the suppliers. Additionally, they estimated key parameters of the order allocation model using time series algorithms and then determined the optimal order allocation to suppliers through mathematical modeling.

(Rostami et al. 2023) evaluated and selected suppliers for medical equipment. They utilized the Viable Supply Chain criteria, which include agility, resilience, sustainability, and digitization, for supplier evaluation. A novel approach combining FBWM with goal programming was used to determine criteria weights, and suppliers were prioritized using the VIKOR method. In another study, (ForouzeshNejad 2023) focused on the issue of supplier selection for medical equipment during the COVID-19 pandemic. They introduced a new approach based on BWM to evaluate suppliers according to agility, sustainability, and Industry 4.0 criteria. (Echefaj et al. 2023) evaluated and selected resilient and sustainable suppliers within the circular economy framework. They presented a qualitative framework tailored to resilience and circular economy criteria.

(Bai et al. 2024) also evaluated and selected suppliers within the circular economy context. They used the BWM method to weigh criteria and proposed a hybrid approach based on Regret Theory (RT) and Dual Hesitant Fuzzy Sets (DHFS) for supplier evaluation and selection. Furthermore, (Siddiquee et al. 2024) developed a framework for evaluating pharmaceutical suppliers, focusing on criteria relevant to emerging markets and economies. Their study revealed that economic factors are significantly more critical than environmental criteria in developing countries and emerging economies. (Zeynali et al. 2024) evaluated suppliers in the agricultural industry with a focus on LARG criteria combined with customer orientation. They weighted supplier evaluation indicators using the stochastic best-worst method and then developed a model to assess supplier performance through machine learning algorithms. Their findings indicate that the criteria “Service level,” “Robustness,” “Cost,” “Quality,” “Manufacturing flexibility,” “Delivery speed,” “Waste management,” and “Restorative Capacity” were identified as the most important factors.

Table 1 summarizes and categorizes the reviewed articles presented in this section.

Table 1
Classification and summary of articles done

Methodology	Case study	Evaluation Criteria			Paper
		Circular Economic	**Resilience**	**Agile**	
FBWM- MULTIMOORA- COPRAS	---				(Tavana et al. 2021)
Mathematical model - novel nRa-NSGA-II	Medical Equipment	×	×		(Shao et al. 2022)
FBWM-FIS-ML	Medicine	×	×		(Sazvar et al. 2022)
BWM - Mathematical model	---		×		(Hosseini et al. 2022)
ANP - PROMETHEE	Chemical production				(Coşkun et al. 2022)
SFBWM – Time Series – Mathematical model	Healthcare system		×		(Nayeri et al. 2023)
Qualitative approach	---	×	×		(Echefaj et al. 2023)
FBWM, Markov, QFD	Online retailer	×	×		(Tavakoli, Tajally, et al. 2023)
Goal Programming based on BWM	Healthcare system		×	×	(Rostami et al. 2023)
RBWM - IR-MABAC	Healthcare system	×		×	(ForouzeshNejad 2023)
BWM-DHFE-RT	---	×			(Bai et al. 2024)
TOPSIS - COA	Pharmaceutical	×			(Siddiquee et al. 2024)
SBWM – Machine Learning	Agri-food		×	×	(Zeynali et al. 2024)
Fuzzy BWM – Weighted SVM	Automotive industry	×	×	×	**This work**

Based on the review of the literature, it is evident that recent studies have paid less attention to the evaluation of suppliers in the automotive industry, making this topic particularly significant in the current study. Additionally, the use of data-driven approaches in articles has been increasing over the past two years. This study adopts advanced and hybrid data-driven decision-making methods, highlighting its innovative aspect in this regard. Moreover, the simultaneous consideration of agility, resilience, and circular economy criteria in supplier evaluation has been rarely explored. This study focuses on integrating these three dimensions into a unified supplier evaluation model, addressing this gap in the literature.

3. Methodology

This section explains the research methodology. In this study, the supplier evaluation criteria are first identified based on agility, resilience, and circular economy indicators, and then finalized to align with the automotive industry. Subsequently, the criteria are weighted using the Fuzzy Best-Worst Method (FBWM), leveraging data collected through questionnaires. After determining the criteria weights, a dataset for developing the supplier evaluation model is created using supplier-related data. The Weighted Support Vector Machine (WSVM) algorithm is then employed to develop a model for supplier evaluation. Overall, the structure and flowchart of the research steps are illustrated in Figure 1.

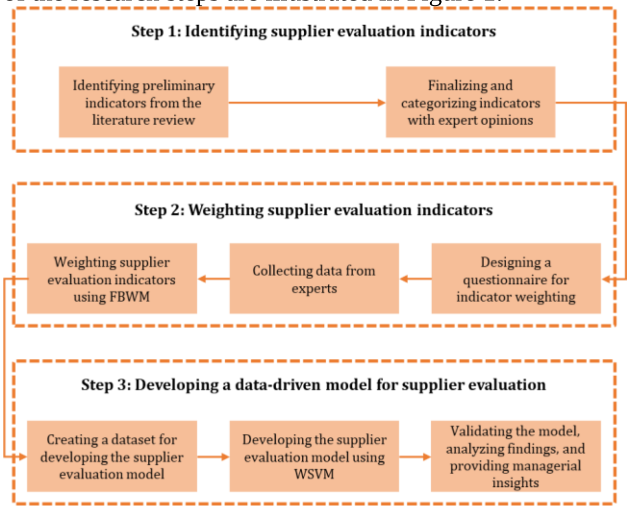

Fig. 1. Flowchart of research steps

The Fuzzy Best-Worst Method and the Weighted Support Vector Machine are explained in the following sections.

3.1. Fuzzy Best-Worst Method (FBWM)

The Fuzzy Best-Worst Method (FBWM) is a multi-criteria decision-making (MCDM) method that combines fuzzy set theory with the Best-Worst Method (BWM) (Nessari et al. 2024; Rezaei 2015). This method is used for weighting criteria or indicators and is particularly effective in scenarios where ambiguity and uncertainty exist in decision-makers' judgments (Tavakoli, Torabi, et al. 2023). In FBWM, the decision-maker first identifies the best and worst criteria, then expresses the relative importance of criteria using triangular or trapezoidal fuzzy numbers. By minimizing inconsistencies in judgments, FBWM determines optimal and consistent weights for the criteria (Rezaei 2016).
The steps for implementing FBWM are summarized as follows (Rezaei 2016):
1. Step 1 (Selection of the Best and Worst Criteria): The decision-maker selects one criterion as the "best" (most important) and another as the "worst" (least important) from the set of criteria.
2. Step 2 (Determining the Importance of Criteria Relative to the Best Criterion - BO): The decision-maker specifies the importance of all other criteria relative to the best criterion using fuzzy values (triangular or trapezoidal numbers). These values are recorded in a comparison matrix.
3. Step 3 (Determining the Importance of the Worst Criterion Relative to Other Criteria - OW): The decision-maker specifies the importance of the worst criterion relative to other criteria using fuzzy values. These values are also recorded in another comparison matrix.
4. Step 4 (Construction of the Fuzzy Pairwise Comparison Matrix): By combining the fuzzy values from BO and OW, a fuzzy pairwise comparison matrix is constructed, representing the relationships between criteria.
5. Step 5 (Solving the Mathematical Model and Determining Fuzzy Weights): A mathematical model is formulated to minimize inconsistencies in judgments. This model is typically designed based on the minimum distance between the BO and OW values. Solving the model determines the fuzzy weights of the criteria.
6. Step 6 (Calculating the Consistency Ratio): The consistency ratio is calculated to ensure that the decision-maker's judgments are consistent.
7. Step 7 (Defuzzification of Weights): The fuzzy weights are converted into crisp values to facilitate analysis and their use in decision-making models.
FBWM reduces judgment inconsistencies by minimizing inconsistencies, thereby enabling more accurate decision-making (Rezaei 2016). Additionally, it requires fewer comparisons compared to other methods (e.g., AHP), making it more user-friendly (Sazvar et al. 2022). In this study, FBWM is used to weight the evaluation criteria.

3.2. Weighted Support Vector Machine (WSVM) Algorithm

The Weighted Support Vector Machine (WSVM) is a modified version of the SVM algorithm that assigns weights to each feature or data point (Huang et al. 2023). These weights represent the relative importance of each feature in the modeling process, allowing the model to focus more on the critical features. WSVM is particularly useful when features have different impacts on prediction or when the dataset is imbalanced (Tavakoli et al. 2024; Yujiao et al. 2023).
The steps for implementing WSVM are as follows (Huang et al. 2023):
1. Step 1 (Data Preparation): The training and testing data are prepared, and features are identified. In this study, the features are the supplier evaluation criteria. Preprocessing steps such as data normalization, outlier removal, and data quality checks are applied to the dataset.
2. Step 2 (Feature Weight Assignment): Each feature is assigned a specific weight based on its importance in the model. The feature weights for WSVM are derived from the FBWM method, which outputs the weights of supplier evaluation criteria as the model's features.

3. Step 3 (Defining the Objective Function): The WSVM objective function is modified to incorporate feature weights as follows:

Min:

$$\left(\frac{1}{2}\right)\sum v_i\|w\|^2 + C\sum \xi_i$$

$Subject\ to$:

$$y_i(w^T v x_i + b) \geq 1 - \xi_i$$

$Where$:

v_i: Weight of feature i
w: Weight vector of the model
ξ_i: Slack variables
C: Penalty parameter

4. Step 4 (Updating Constraints with Weights): The constraints are defined such that the feature weights influence the decision boundary.
5. Step 5 (Solving the Optimization Problem): The WSVM problem is solved using Quadratic Programming (QP) optimization methods in this study.
6. Step 6 (Model Evaluation): The model is evaluated on the testing data to assess its performance. Metrics such as accuracy, F1-Score, and others are used to analyze its effectiveness.
7. Step 7 (Hyperparameter Tuning): Parameters such as C are adjusted to improve model performance. In this study, hyperparameter tuning is conducted using the Grid Search method.
8. Step 8 (Interpreting Weights and Results): The feature weights are analyzed to determine which features have the most significant impact on predictions. This step provides valuable managerial and operational insights.

WSVM offers several advantages due to its ability to account for the relative importance of features, reduce noise effects, and manage imbalanced data with high flexibility (Yujiao et al. 2023). These characteristics make it a powerful tool for supplier evaluation in this study.

4. Case Study and Evaluation Criteria

The automotive industry heavily relies on a robust and efficient supply chain to ensure the consistent production and delivery of high-quality vehicles. This study focuses on evaluating suppliers in the automotive sector, with data sourced from an auto parts manufacturing company. The vendor list of this company includes nine domestic suppliers and eight international suppliers. These suppliers are evaluated periodically, and at the end of each evaluation cycle, three suppliers are selected. The goal of this study is to develop a data-driven model that can identify the top three suppliers in each cycle by inputting data values related to each supplier according to the evaluation criteria.

The 17 potential suppliers of the company under study have been collaborating with the company for over 10 years. For model development, quarterly data from nine years of operations have been used. In other words, the 17 suppliers have quarterly records, resulting in four data entries per supplier per year, amounting to 612 data records over nine years. Based on this dataset, a data-driven model is developed.

As stated in the introduction, to ensure a comprehensive and effective evaluation, this study considers agility, resilience, and circular economy principles as the main criteria. Agility reflects the suppliers' ability to adapt quickly to changes in demand or disruptions. Resilience evaluates the capability to recover from unexpected shocks and maintain the continuity of the supply chain. Circular economy principles emphasize sustainability, assessing suppliers' contributions to resource efficiency, waste reduction, and recycling initiatives.

Evaluation indicators were identified using relevant sources and are categorized under each criterion. These indicators were identified using the articles (Foroozesh et al. 2019; ForouzeshNejad 2023; Jain and Singh 2020; Lee and Moon 2024; Nayeri et al. 2023; Rostami et al. 2023; Sazvar et al. 2022; Stević et al. 2020; Tavakoli, Tajally, et al. 2023) and are detailed in Table 2.

Table 2.
Supplier evaluation indicators in different categories

Dimension	Code	Indicator	Definition
Agility	C01	Delivery Speed	Average Delivery Time of Orders
	C02	Lead Time Flexibility	Flexibility in Delivering Unexpected Orders
	C03	Responsiveness	Supplier's Ability to Respond Quickly and Appropriately to Changes in Demand
	C04	Order Volume Flexibility	Supplier's Ability to Adjust Order Volume and Fulfill Requirements
	C05	Quality	Quality of the Target Product Supplied by the Supplier
Resilience	C06	Excess Inventory	Having excess inventory storage for urgent situations
	C07	Backup Supplier	Capability to contract with backup suppliers
	C08	Reliability	Supplier's ability to respond effectively in critical situations
	C09	Collaboration	Supplier's ability to collaborate with supply chain partners and stakeholders
Circular Economy	C10	Reusability	Reusability of products within the recycling chain
	C11	Repairability	Repairability of products manufactured by the supplier
	C12	Waste Reduction	Supplier's ability to minimize waste generation in production processes
	C13	Energy Efficiency	Optimal energy usage in production processes and reduction of energy consumption
	C14	Price	Final price offered by the supplier for the target product

Based on the descriptions of the evaluation indicators shown in Table 2, each data record includes the values corresponding to the indicators as well as the supplier label. Using these data and the Weighted Support Vector Machine (WSVM) algorithm, the suppliers are evaluated.

5. Findings

This section reports the findings of the study. First, the supplier evaluation indicators are weighted. Subsequently, using the collected dataset and the WSVM algorithm, a model is developed to evaluate suppliers. This model enables the assessment of suppliers based on the provided data. Additionally, a sensitivity analysis of the model's indicators and an evaluation of the algorithm's accuracy are conducted.

5.1. Weighting indicators using FBWM

The FBWM method was used to weight the evaluation indicators. The required data were collected through a questionnaire distributed to 13 experts, including senior managers in the automotive industry, consultants and specialists in this field, as well as academics and researchers in the supply chain domain. The collected data were processed, and the indicator weights were calculated using the Fuzzy Best-Worst Method. The results are presented in Table 3. The findings show that the resilience category holds the highest importance among the criteria. Among the sub-indicators, excess inventory and backup supplier are identified as the most critical indicators.

Table 3
The weight of supplier evaluation indicators

Dimension	Weight	Indicator	Internal Weight	Final Weight
Agility	0.3138	Delivery Speed	0.2004	0.0629
		Lead Time Flexibility	0.1894	0.0594
		Responsiveness	0.1923	0.0603
		Order Volume Flexibility	0.1871	0.0587
		Quality	0.2309	0.0725
Resilience	0.3473	Excess Inventory	0.2632	0.0914
		Backup Supplier	0.2570	0.0892
		Reliability	0.2477	0.0860
		Collaboration	0.2322	0.0806
Circular Economy	0.3389	Reusability	0.1946	0.0660
		Repairability	0.1995	0.0676
		Waste Reduction	0.2019	0.0684
		Energy Efficiency	0.1971	0.0668
		Price	0.2068	0.0701

The FBWM method's validation is conducted using the consistency ratio, which must be less than 0.1. The consistency ratios for the comparisons are as follows: 0.0351 for the dimensions, 0.0743 for agility indicators, 0.0581 for resilience indicators, and 0.0492 for circular economy indicators. Therefore, the questionnaire data are valid.

5.2. Supplier evaluation using WSVM

In this section, the supplier evaluation model is developed using the WSVM algorithm. As mentioned in the case study section, 612 data records are utilized for this purpose, with each record containing values for 14 supplier evaluation features along with their corresponding labels. To build the model, 80% of the data is used for training, and 20% is reserved for testing. In the first step, the relationships between the features are examined. For this purpose, the correlation coefficient is used, as shown in the heatmap in Figure 2. Figure 2 illustrates those certain features, such as energy efficiency and waste reduction, have a positive correlation. This suggests that suppliers excelling in energy efficiency typically also perform well in waste reduction. Additionally, while it might be expected that quality and price would have a negative correlation, no significant correlation is observed in this dataset. This could indicate the presence of suppliers offering high-quality products at competitive prices.

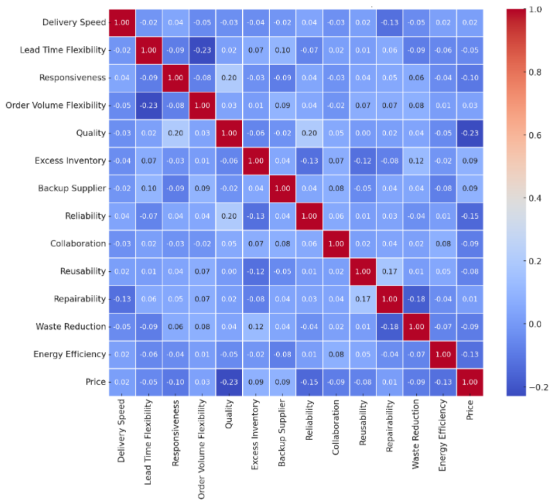

Fig. 2. Heatmap matrix of relationships between features

Based on the data, the WSVM model was developed, as illustrated in Figure 3, which presents the structure of the algorithm and the decision boundaries in a combined scenario. This diagram visualizes the decision boundaries of the WSVM algorithm in a space defined by two

principal components (PCA). Each colored region in the image represents a class of suppliers (selected, reserve list, or rejected) where the algorithm makes decisions.
The training data are displayed in different colors according to their actual classes, while the red points, identified as support vectors, are specific samples that directly influence the shape of the decision boundaries. These points are typically located near the decision boundaries and are crucial for the algorithm, as they determine how the data are separated.

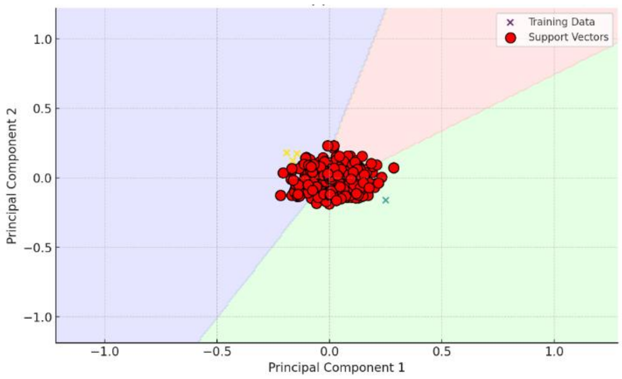

Fig. 3. Demarcation diagram between labels data

Using the developed algorithm, the 17 suppliers were evaluated. Table 4 presents the evaluation results, showing that 5 suppliers were selected, 7 suppliers were placed on the reserve list, and 5 suppliers were rejected.

Table 4
Evaluation of suppliers with WSVM

Supplier	Evaluation status	Supplier	Evaluation status
S01	Selected	S10	Reserve
S02	Rejected	S11	Reserve
S03	Reserve	S12	Reserve
S04	Rejected	S13	Rejected
S05	Rejected	S14	Selected
S06	Selected	S15	Selected
S07	Rejected	S16	Reserve
S08	Reserve	S17	Reserve
S09	Selected		

5.3. Validation of the WSVM Model

The validation of the WSVM algorithm was performed using a confusion matrix and the accuracy metric. As shown in Figure 4, out of the 123 test data points, the labels of more than 90% of the cases were correctly predicted. For the misclassified instances, the differences between the predicted and actual labels were minimal. Therefore, the performance of the algorithm demonstrates a high level of accuracy, indicating its reliability for supplier evaluation.

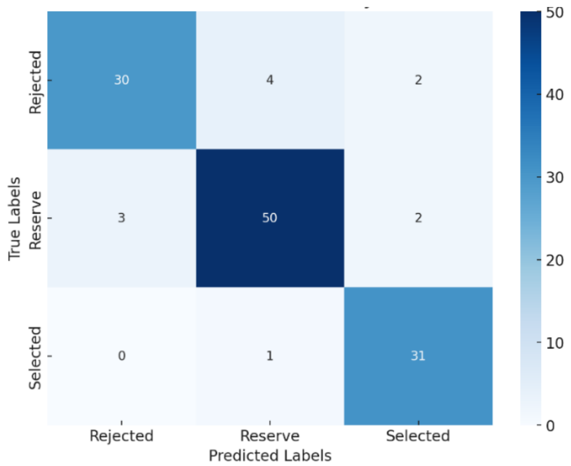

Fig. 4. Confusion matrix

Additionally, the accuracy metric was used to calculate the algorithm's precision. The evaluation results indicate that the model achieved an accuracy of 90.35%, demonstrating the algorithm's effectiveness. In other words, the developed WSVM algorithm is capable of evaluating supplier performance with an accuracy exceeding 90%.

5.4. Managerial insights

As highlighted in various sections of the paper, in the highly challenging environment of the automotive industry, suppliers play a critical role in the overall performance of the supply chain. This study demonstrates that employing hybrid data-driven models like the WSVM algorithm can enhance the accuracy of supplier evaluations. The approach indicates that combining expert opinions with real data improves the algorithm's precision. Moreover, evaluating the performance of automotive industry suppliers necessitates considering a variety of indicators. This study incorporated agility, resilience, and circular economy principles, with resilience and circular economy indicators being the most significant.
This research clearly underscores the importance of hybrid approaches in supplier evaluations. Managers should prioritize concepts such as agility and resilience alongside traditional indicators like cost and quality to effectively respond to changes and crises. Furthermore, incorporating circular economy principles in supplier selection provides an opportunity to strengthen corporate social responsibility and reduce environmental impacts. Employing this model can help companies maintain their competitiveness in global markets and adapt to the dynamic changes in the business environment.

6. Conclusion

This research aimed to present a comprehensive model for evaluating and selecting suppliers in the automotive industry, integrating agility, resilience, and circular economy principles. Through a literature review, 14 indicators (5 agility indicators, 4 resilience indicators, and 5 circular economy indicators) were identified and weighted using expert opinions, questionnaires, and the FBWM method. The findings reveal that the resilience category is the most critical group of indicators, with excess inventory and backup supplier being the most important indicators for evaluating automotive suppliers. Additionally, using documented data and the hybrid WSVM method, a model was developed that evaluates suppliers with an accuracy of approximately 91%. This result demonstrates that employing hybrid data-driven methods in supplier performance evaluation enhances decision-making accuracy.

In this study, data-driven approaches are combined with multi-criteria decision-making methods. These approaches enhance the accuracy of evaluations. Many studies in this field have relied on expert-driven approaches, where evaluations are conducted through expert surveys (Hajiaghaei-Keshteli et al. 2023; Rostami et al. 2023; Tavakoli, Tajally, et al. 2023). However, this study adopts data-driven approaches, which improve the model's performance in terms of accuracy and speed in supplier evaluation. This approach has been utilized in studies such as (Sazvar et al. 2022; Zeynali et al. 2024). Therefore, the use of data-driven approaches has demonstrated high efficiency and has gained significant attention from researchers in recent years. This study also recommends the adoption of data-driven approaches. Future studies are recommended to develop other data-driven algorithms based on machine learning for supplier evaluation. Additionally, other dimensions such as digitization should be considered in supplier assessments.

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