



Research article

Financial analysis and sustainability from a multi-criteria perspective in the automotive sector

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Abstract: To overcome the limitations of one-dimensional rankings and subjective expert-based evaluations, we introduced an objective multi-criteria framework for assessing corporate performance in the global automotive sector. The approach integrated financial indicators with Environmental, Social, and Governance (ESG) scores for a dataset of 430 manufacturers. Performance ranking was conducted using Extended Goal Programming (EGP), while Rough Set Theory (RST) was employed for group classification. The results indicated that the EGP model effectively identifies top-performing firms demonstrating balanced excellence across financial profitability and sustainability dimensions. Sensitivity analysis further revealed that ESG performance serves as the key differentiator under varying stakeholder priorities. Moreover, the RST classification framework substantially outperforms conventional Support Vector Machine (SVM) models, achieving accuracy levels around 90% compared to 80.95% obtained in the SVM model. This indicated that rough set model robustly addresses uncertainty and indiscernibility of data within industry-specific financial variables. The application of these methodologies provides investors and managers with a rigorous, data-driven tool for strategic benchmarking and sustainability-oriented decision-making.

Keywords: Sustainability; goal programming; rough set; rankings; automotive sector

JEL Codes: M14, N70, R40

1. Introduction

The automotive industry is undergoing its most significant transformation since the invention of the combustion engine. Driven by global decarbonization targets and the transition to electric mobility, environmental, social, and governance (ESG) factors have moved from the periphery of corporate strategy to the core of financial valuation. For stakeholders in this capital-intensive sector, traditional financial analysis is no longer sufficient. Thus, there is a need to add tools to evaluation models to combine traditional profitability metrics with sustainability performance. In the automotive industry, rankings are fundamental tools for analyzing and comparing companies. These rankings can incorporate a range of variables, including annual sales, CO₂ emissions, economic and financial indicators, and sustainability factors such as ESG scores. While one-dimensional rankings are straightforward to construct and interpret, they focus analysis on a single variable, thereby failing to capture the complex inter-relationships among important company characteristics. This limitation can result in partial interpretations and suboptimal decision-making, as shown by Greco et al. (2016). This simplification is critical in sectors where there is a certain convergence in different technical, economic, social, and environmental dimensions. As a result, stakeholders may develop a biased perspective when analyzing rankings that reflect only a single variable, which can negatively impact investment decisions, policymaking, and consumer behavior (Velasquez & Hester, 2013). This limited scope makes it challenging for stakeholders to perform a holistic analysis, as companies' relative positions may differ greatly depending on which variable is considered.

In contrast, multi-criteria rankings provide a robust alternative, enabling the joint analysis of various company dimensions. Based on the principles of Multi-Criteria Decision Analysis (MCDA), these rankings integrate and weigh multiple relevant indicators. Popular methods in this field, such as the Analytic Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to the Ideal Solution (TOPSIS), have been successfully applied in automotive technology selection, including comparisons between electric and internal combustion vehicles (Mardani et al., 2015; Ziemba, 2021). This approach enables simultaneous consideration of economic and sustainability criteria, reducing bias inherent in one-dimensional rankings and offering a more holistic view. However, multi-criteria models can face discernibility challenges when metrics of compared variables are very close. For example, manufacturers with similar energy efficiency or safety levels might be difficult to distinguish accurately, diminishing ranking robustness. To address this, enhancements such as entropy-based measures, dispersion criteria, or hybrid MCDA methods combined with machine learning have been proposed to increase discriminatory power (Kügemann et al., 2020). Moreover, integrating sustainability criteria remains a priority for stakeholders aiming to broaden perspectives beyond purely economic factors. Stoycheva et al. (2018) illustrated this by proposing an MCDA framework that incorporates sustainability metrics and applies sensitivity analysis to reinforce ranking robustness in automotive material selection. Hence, multi-criteria rankings are vital tools to analyze, compare, and forecast industry performance amid ongoing innovation, regulatory tightening, and rising sustainability demands (Ferdous et al., 2024).

In this paper, we attempt to answer the following questions:

- Can multi-criteria mathematical framework provide a more objective and robust performance ranking of automotive companies than traditional single-dimension indices?
- To what extent do sustainability (ESG) scores influence a firm's overall competitive standing when compared to traditional financial indicators?
- Can non-linear, rule-based classification models accurately predict a company's ESG performance level based solely on its financial characteristics?

To answer the first two questions, we apply a goal programming (GP) methodology to develop a multi-criteria ranking that incorporates ESG scores for automotive companies. This produces a ranking that analyzes financial variables and ESG data together and simultaneously. This enables a more comprehensive analysis of companies, avoiding the biases that arise when analyzing one-dimensional rankings of financial indicators. To answer the last question, we employ the rough set methodology to enhance group discrimination, addressing indiscernibility issues due to closely related variables within the sector. The model's performance is evaluated by comparing it with the traditional Support Vector Machine (SVM) classification model. In this case, the application of non-linear classification models can improve predictive capacity in ESG score classification based on financial variables. Furthermore, in the case of the proposed methodology, rough set improve results compared to SVMs, taking into account that many financial variables may not be discernible between companies in order to perform their ESG classification.

The remainder of the paper is structured as follows: In Section 2, we present the principal literature review. In Section 3, we detail the methodologies and models employed in the study. In Section 4, we present the major results obtained for the automotive sector sample. Finally, in Section 5, we discuss conclusions and outline potential improvements and directions for future research.

2. Literature review

The automotive industry plays a key role in driving technological innovation and economic growth. The financial dynamics of the sector are of vital importance to a wide range of stakeholders, including investors, managers, and policymakers, who rely on financial indicators to assess the viability and profitability of companies. Structural changes, particularly the rapid advancement of electric and hybrid vehicles, have transformed the industry landscape. Operating in an evolution and changing consumer preferences, automotive companies face increasing pressure to achieve sustainable growth and profitability. In this context, financial indicators remain essential tools for assessing a company's operational efficiency, liquidity, and overall economic performance (Putri et al., 2024). Nevertheless, these transformations in the sector industry caused by advances in technology, the evolution of environmental regulations, changing customer expectations, and cost-efficiency, require management to implement effective strategies in all processes. These strategies should enable the achievement of essential corporate objectives, such as profitability, competitiveness, and long-term sustainability. In other words, it is necessary to incorporate ESG values within companies (Tadić and Komatina, 2025). Thus, historical unsustainable corporate practices in this sector and excessive resource consumption have exacerbated the interest and the obligation to adopt greener and more responsible approaches. In addition to environmental concerns, social aspects like labor conditions and inclusion have driven companies to improve transparency and responsibility. Of course, Governance related matter, including board diversity and corporate ethics have become key indicators of

organizational integrity (Mahanta et al., 2024). Consequently, the integration of sustainable business practices has emerged as strategic imperative in today's competitive landscape.

In the automotive industry, rankings have become an important resource for analyzing and comparing the performance of manufacturers, brands, and vehicle models. Depending on the criteria selected for comparison, different rankings can be established. However, these one-dimensional rankings enable only the analysis of a single dimension, variable, or characteristic, such as annual sales and CO₂ emissions. Thus, this type of one-dimensional ranking has some advantages, such as ease of preparation, analysis, understanding, and dissemination. Nevertheless, they have limitations, such as the difficulty of understanding more complex processes, given that the individualized analysis of variables can lead to information bias. Therefore, decision-making may be inadequate due to misinterpretation of the information (Greco et al., 2016). This simplification becomes particularly critical in a sector where multiple technical, economic, social, and environmental dimensions converge. Thus, a ranking focused on a single variable does not provide sufficient information for decision making, and it can be relatively complex to analyze multiple one-dimensional rankings to obtain a clear idea of a company's position in the sector. As a result, the various actors who make decisions based on these rankings may reach biased conclusions, affecting investment processes, public policy design, or consumption patterns (Velásquez & Hester, 2013).

On the other hand, multi-criteria rankings represent a more efficient alternative. Most of these rankings are based on multi-criteria decision analysis (MCDA)/multi-criteria decision making (MCDM), which enables different relevant dimensions to be integrated and weighted. Some of the most widely used multi-criteria models in the automotive sector have been the AHP, the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), and fuzzy versions. Their most recent use has been linked to decision-making on technology selection, especially when comparing electric vehicles with internal combustion models (Mardani et al., 2015; Ziemba, 2021). This approach makes it possible to simultaneously assess economic, environmental, safety, and innovation criteria, which helps reduce the bias inherent in one-dimensional rankings and offers a more comprehensive and realistic view. However, even in multi-criteria models, an additional challenge remains: Limited discernibility between variables.

In many cases, the metrics used to evaluate alternatives are very similar, making it difficult to distinguish performance groups. For example, when different manufacturers achieve similar levels of energy efficiency or safety, traditional ranking methods can generate results that are not very discriminating, in which the hierarchy loses statistical robustness. This challenge has led to the introduction of advanced techniques within MCDA, such as the use of entropy measures, dispersion criteria, or hybrid methods that combine MCDA with machine learning algorithms to increase discriminatory power and improve the robustness of rankings (Kügemann et al., 2020).

For stakeholders, incorporating multi-criteria approaches with robust discernibility mechanisms represents a strategic advantage. Manufacturers can prioritize investments in areas where small technical differences make a significant competitive advantage. For instance, regulators obtain more stable ratings, which are useful for defining minimum standards and public policy guidelines, and consumers have access to clearer and more reliable information, which reduces confusion in markets with highly similar products. Finally, investors have tools that enable them to more accurately differentiate companies that truly excel in sustainability, innovation, or safety, avoiding decisions based on superficial or poorly differentiated metrics.

In this regard, Stoycheva et al. (2018) proposed an MCDA framework aimed at selecting materials in the automotive industry, in which they integrated sustainability criteria and applied sensitivity analysis to ensure the robustness of the ranking. This work demonstrates how decisions based on multi-criteria methodologies can build trust among decision-maker profiles.

The application of the multi-criteria GP methodology appears to be a solution to the problem indicated above. This methodology has been used to create rankings of many different kinds. For example, García et al. (2010) created an index of Spanish savings banks, taking into account economic and financial variables. It has also been used to analyze the classification of microfinance institutions (Cervelló-Royo et al., 2017) and to create rankings that take into account issues of corporate social responsibility (CSR). Some examples can be found in Guijarro and Poyatos (2018), who compare the sustainability of European Union countries. On the other hand, García-Martínez et al. (2017) analyzed the social responsibility of European companies.

Among the advantages of using the GP methodology in ranking, it is worth noting that it does not require the use of a panel of experts, unlike other multi-criteria tools, which undoubtedly incorporate subjectivity, both in determining the criteria and in the weightings. Charnes and Cooper (1957) proposed this methodology in which the functions may or may not be linear, using continuous and discrete variables that are subsequently transformed into different goals (Ignizio et al., 2003). The purpose of GP is to reduce the gap between the objectives achieved and the level of achievement of those that had been initially set (Romero, 2001). GP enables a series of differentiated objectives to be obtained jointly. Furthermore, it is particularly effective when it is not possible to obtain a defined utility function (maximization or minimization), as it brings the achievement of each of the objectives as close as possible, reducing the gap between them (Tamiz et al., 1998).

In conclusion, although one-dimensional rankings have been widely disseminated, they are limited in their ability to reflect the complexity of the automotive industry and provide useful information to the players in the sector. Given this shortcoming, multi-criteria rankings, based on statistical methodologies of MCDA/ MCDM, not only enable the integration of relevant criteria, but also address the challenge of discernibility between variables. In this way, they offer more equitable and consistent assessments that are aligned with the strategic needs of the automotive sector. Consequently, they are essential tools for analyzing, comparing, and projecting the industry's performance in a context marked by constant innovation, tighter regulations, and growing demands for sustainability (Ferdous et al., 2024).

3. Materials and methods

In section, we outline the methodologies employed in this study. First, GP is presented as a means of constructing a multicriteria ranking for the automotive sector. The main advantage of this approach is that it enables stakeholders to assess economic and financial dimensions of companies simultaneously, including ESG scores. Standard rankings enable only the analysis of a single variable, thus limiting the overall analysis. Once the multi-criteria ranking has been constructed, it may be necessary to apply discretization methodologies to distinguish, based on economic and financial data, whether the company is sustainable and to create groups or categories according to the level of sustainability. Two methodologies are presented in this regard. The first is the Rough Sets model, which is a classification technique that considers the uncertainty inherent in the data and identifies useful decision rules to discriminate companies with different degrees of sustainability. Then, this model will be compared with the classic SVM classification model.

3.1. GP model

To construct a ranking, it is necessary to select the criteria to be used and to assign a weighting to each of them. It is common to find rankings in which the criteria used are described correctly, but the weightings are treated in an unclear or vague manner. This means that the information represented in the ranking may be biased and not very objective. Moreover, this problem is exacerbated when we attempt to construct rankings that take multiple criteria into account simultaneously. There are some examples, such as in the major university rankings, where clear and detailed information on the methodology used and the calculation of the different weights of each criterion is not provided (Adenle et al., 2020; García, 2020). In contrast, other rankings provide a clear explanation of the methodology used, employing a panel of experts in conjunction with the AHP. This approach can also lead to subjectivity in the process (Lukman et al., 2010; Gómez et al., 2015; Adenle et al., 2020; Aliyev et al., 2020; Ozdemir et al., 2019).

It is a common assumption in the field that each criterion used in a ranking belongs to a single dimension. Furthermore, it has only one weighting. However, it should be noted that there may be criteria that belong to different dimensions. In this case, determining whether these are independent of each other becomes a more complex process, as does calculating the corresponding weightings. GP is an effective solution to this problem. This multi-criteria methodology has been employed in numerous fields, not only in the creation of rankings. For instance, García et al. (2010) applied GP using financial variables from Spanish financial institutions to create an index. Cervelló-Royo et al. (2017) applied GP to the analysis and classification of microfinance institutions. Guijarro and Poyatos (2018) provided some examples of the application of GP in the creation of ranking, analyzing the sustainability of European Union countries. García-Martínez et al. (2017) also analyzed the social responsibility of European companies.

One of the key benefits of implementing GP in the creation of rankings is that it does not necessitate the involvement of a panel of experts. As stated, these experts may introduce subjectivity and bias into the process. Another interesting advantage is the elimination of the assumption of independence between the dimensions. This feature enables a criterion to be assigned to multiple dimensions.

The GP methodology was proposed by Charnes et al. in 1957. It employs continuous and discrete variables that are subsequently converted into different objectives, along with linear and non-linear functions (Ignizio et al., 2003). The primary objective of this methodology is to minimize the discrepancy between objectives achieved and the degree of achievement (Romero, 2001). GP is a tool that can be used to achieve multiple objectives simultaneously, with the aim of achieving the smallest possible difference between the objective achieved and the desired degree of achievement. In instances where a clear utility function cannot be defined (i.e., maximization or minimization), this methodology enables us to approximate each objective and its desired level of achievement as closely as possible. This approach serves to minimize the disparities between them (Tamiz et al., 1998).

3.1.1. Data normalization

Prior to implementing the GP models, all variables should be normalized to a common scale ranging from 0 to 1. This normalization ensures that indicators with large absolute magnitudes do not disproportionately influence the computed weights. The normalized value ($crit_{ij}^*$), equation 1,

corresponding to the j -th criterion of the i -th company is obtained using the min-max normalization method:

$$crit_{i,j}^* = \frac{crit_{i,j} - crit_j^{min}}{crit_j^{max} - crit_j^{min}} \quad (1)$$

where:

- $crit_{i,j}$ is the original value.
- $crit_j^{min}$ and $crit_j^{max}$ are the minimum and maximum values of criterion j across the sample.

3.1.2. Goal programming formulations

As outlined, one of our objectives of this study is to construct a multi-criteria ranking of companies in the automotive sector, considering financial variables and ESG scores. The performance of automotive companies is determined by a set of criteria, selected using a linear function. In other words, the primary objective of the model is to compute a unified multi-criteria performance score ($perV_i$) for each company i (Equation 2). This score is derived as a weighted sum of the company's normalized criteria (García et al., 2021):

$$perV_i = \sum_{j=1}^d w_j crit_{i,j}^* \quad (2)$$

in which:

- $perV$ is the multi-criteria performance of the i -th company.
- $crit_{i,j}^*$ is the normalised value of the j -th selected criterion of the i -th company.
- w_j is the weight of the j -th selected criterion.

There are three variations of the GP model for calculating weights and the performance score. In this way, the weights w_j assigned to the selected criteria are calculated more objectively. Thus, it is possible to construct a multi-criteria ranking avoiding the biases of using expert panels, as in other methodologies.

Weighted Goal Programming (WGP)

The WGP model aims to derive a set of "consensus" weights by minimizing the total absolute deviations between the estimated multi-criteria performance ($perV_i$) and the observed performance values for each criterion ($crit_{i,k}^*$). Therefore, weights are calculated by attempting to minimize the gap between the multi-criteria result achieved and the individual objectives (goals) for each criterion. The model can be expressed as follows:

$$\min \sum_{i=1}^n \sum_{k=1}^d (\alpha_k n_{ik} + \beta_k p_{ik}) \quad (3)$$

$$s. t. \quad \sum_{j=1}^d (w_j crit_{i,j}^*) + n_{ik} - p_{ik} = crit_{i,k}^* \quad i = 1 \dots n, \quad k = 1, \dots d \quad (4)$$

$$\sum_{j=1}^d w_j = 1 \quad (5)$$

$$\sum_{j=1}^d w_j \text{crit}_{i,j}^* = \text{per}V_i \quad i = 1 \dots n \quad (6)$$

$$n_{ik}, p_{ik}, w_j \geq 0 \quad (7)$$

As is evident, the objective function (Equation 3) includes negative (n_{ij}) and positive (p_{ij}) deviations between the multi-criteria result or score and the individual criteria for the i -th company and for the k -th criterion. To enable the model to differentiate these deviations, coefficients α_j and β_j are employed, where the former takes a value of 1 if the negative deviations (n_{ij}) are not accepted and a value of 0 otherwise. The latter coefficient will take a value of 1 if the positive deviations (p_{ij}) are not accepted and 0 otherwise. The next equation (Equation 4) quantifies the difference by excess (defect) between the value of the i -th company in the k -th criterion and the multicriteria values obtained (García et al., 2010).

Conversely, w_j is the weight calculated for each criterion, considering the deviations mentioned above. As can be seen, these weights do not require the participation of any panel of experts, thus avoiding any bias or subjectivity. This does not imply that the presence of experts is not necessary, as it is necessary to select the desired criteria for constructing the ranking. The sum of these weights must be equal to one (Equation 5); the variables that collect the deviations (n_{ij} , p_{ij}) in the minimization objective function. The following equation (Equation 6) has been explained above (Equation 2). It should be noted that all variables must be positive (Equation 7).

MinMax model (Chebyshev model)

The Chebyshev GP model was presented by Flavell (1976). This model uses the underlying Chebyshev means of measuring distance (Gupta et al., 2015). The MINMAX model can work with completely opposing criteria (Romero, 2001). This means that it emphasizes the treatment of discordant criteria. Moreover, rather than aggregate the sum of deviations, it seeks to minimize the maximum deviation (D) observed across all criteria, thereby ensuring that no single indicator has a dominant influence on the solution (Equation 8). The model could be expressed as:

$$\min D \quad (8)$$

$$\text{s. t. } \sum_{j=1}^d (w_j \text{crit}_{i,j}^*) + n_{ik} - p_{ik} = \text{crit}_{i,k}^* \quad i = 1 \dots n, \quad k = 1, \dots, d \quad (9)$$

$$\sum_{i=1}^n (\alpha_{ij} n_{ik} + \beta_{ij} p_{ik}) \leq D \quad k = 1 \dots n \quad (10)$$

$$\sum_{j=1}^d w_j = 1 \quad (11)$$

$$n_{ik}, p_{ik}, w_j \geq 0 \quad (12)$$

$$\sum_{j=1}^d D_j = Z \quad (13)$$

Equation 9 has been explained above, being identical to equation 4. In the subsequent constraint (Equation 10), D represents the overall deviation between each criterion and the estimated multi-criteria result for each company. Furthermore, Equations 11 and 12 are similar to equations 5 and 7. Finally, in equation 13, Z summarizes the overall discrepancies. Thus, a low value would indicate that the estimated multi-criteria result is consistent with the performance or objectives of the individual criteria. In other words, the gap or deviation will be small. On the other hand, a high value of Z represents a very high and significant deviation. This generally occurs when the criteria have a lower correlation with each other. In this case, the results obtained by this model are usually quite weak, since when the function obtained attempts to minimize the distance from the individual criteria globally, some conflicts arise in which the improvement of one leads to worsening of another.

Extended Global Programming (EGP)

One of the first differences, as mentioned above, appears in the objective function. On the other hand, in the MINMAX model, a new constraint appears that calculates D as the sum of the deviations, negative (n_{ij}) and positive (p_{ij}), produced between the multi-criteria result and the individual criteria for the i -th company and for the j -th criterion with the associated coefficients α_j and β_j , which is nothing more than the objective function of the WGP model. Thus, while the WGP model seeks a general consensus among the results of a single criterion, the MINMAX model gives greater weight to the objectives obtained from conflicting criteria.

The EGP model (Romero, 2001) enables a generalization of the two previous models combining both approaches. To do this, parameter λ is introduced, which balances the solutions between both models (WGP and MINMAX). Thus, parameter λ varies between 0 and 1. When λ reaches a value equal to 1, the EGP model obtains the same solutions as the WGP model. If λ obtains a value of 0, the model obtains the same solutions as the MINMAX model. This enables the decision-maker to explore the trade-off between a consensus-base ranking (WGP) and a discordance-based ranking (MINMAX). This extended model (EGP) can be written as:

$$\min \lambda \sum_{i=1}^n \sum_{j=1}^d (\alpha_j n_{ij} + \beta_j p_{ij}) + (1 - \lambda)D \quad (14)$$

And is subject to the same constraints as the WGP and MINMAX models. Given the flexibility of this model (Equation 14), it will be used in this study to create a ranking of companies in the automotive sector, considering economic and financial criteria, as well as each company's ESG scores.

3.2. Rough set model

The theory of ambiguous data set analysis was developed by Pawlak (1982, 2002). This theory analyses the relationships between variables when uncertainty arises, which generally leads to inaccurate results if linear models (regression) are used. A set of variables can be used to identify patterns and select and group their characteristics.

Any information system (U, A) can be defined as a set of objects (U) and a set of attributes (A) . A decision system (T) (Equation 15) relates objects and their attributes through a decision variable that identifies those characteristics not included in the attributes (A) (Sumalatha et al., 2016).

$$T = (U, A \cup \{d\}) \quad d \notin A \quad (15)$$

All elements in set A have several conditional attributes. That is, the relationship between a variable and its decision attribute is conditional. When a series of attributes is selected, a subset (B) of A ($B \subseteq A$) is generated that is related in a binary manner. This is called the IND (B) indiscernibility relation on set U . This relation is generated by two objects, X_i and X_j , that are equal in each element of an attribute on set B (Equation 16). Thus, two objects are indiscernible when:

$$b(X_i) = b(X_j) \quad b \in B \quad (16)$$

For the T decision system with a set of attributes $B \subseteq A$, and for a variable $X \subseteq U$, it is possible to use the information in the set of attributes (B) to try to reduce the distance and approximate the characteristics of the variable. To do this, it must be analyzed whether this approximation to the variable (X) occurs from one external source or another (Equations 17 and 18). That is, whether it is done from below, B-lower (B_*), or from above, B-upper (B^*). These approximations can be defined as:

$$B_*(X) = \bigcup_{x \in U} \{B(x) : B(x) \subseteq X\} \quad (17)$$

$$B^*(X) = \bigcup_{x \in U} \{B(x) : B(x) \cap X \neq \emptyset\} \quad (18)$$

These approximations depend on the different subsets or partitions of U/B and their relationship to the different indiscernible attributes that exist within that set related to the attributes that are indiscernible within that set. For example, the B-superior approximation presents all those relationships that are indiscernible that are found in the non-empty intersection with the set of attributes (Equation 19).

$$BN_b(X) = B^*(X) - B_*(X) \quad (19)$$

Figure 1 shows the approximations to variable X (B-upper and B-lower). This boundary region, B , depends on whether variable X is exact or not with respect to the set of attributes of B . Thus, if the boundary region is $BN_B(X) = \emptyset$, this implies that the value of X would be an exact value with respect to set B . Conversely, when the boundary region B is $BN_B(X) \neq \emptyset$, then X will be an inexact or approximate object with respect to B .

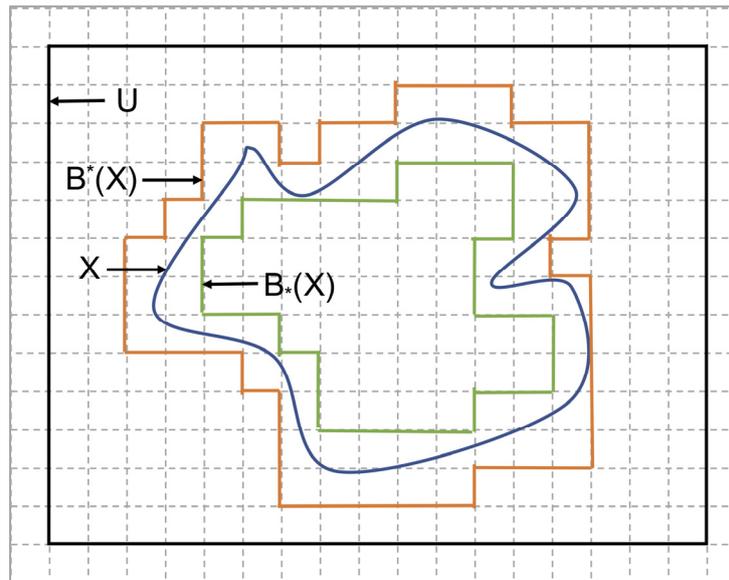


Figure 1. Diagram of domain U , set X , and upper and lower approximations B . *Source: Own elaboration.*

Every information system has two types of attributes: The first type represents conditions, and the second type represents decision attributes (Salama et al., 2011). Both conditions and attributes belong to disjoint sets. This creates a decision-making system defined as $T = (U, A \cup \{d\})$, where $d \in A$. As mentioned above, U is the global set of objects $\{X_1, X_2, X_3, \dots, X_n\}$, A represents the set of condition attributes $\{a_1, a_2, a_3, \dots, a_n\}$, and D is the set of decision attributes $\{d_1, d_2, d_3, \dots, d_n\}$. The decision rule generates the sequence $A \rightarrow_x D$ where x indicates the degree of relationship and dependency between D and A . This decision rule is defined by the intersection between the two sets called $support_x(A, D) = |A(x) \cap D(x)|$, where:

$$\sigma_x(A, D) = \frac{supp_x(A, D)}{|U|} \quad (20)$$

The coefficient $\sigma_x(A, D)$ (Equation 20) has a value between 0 and 1, ($0 \leq \sigma_x(A, D) \leq 1$), which determines the importance of the decision rule and measures the proportion of participation of each of the objects classified in the U/D partition. However, there are a multitude of pairs of relationships between attributes and, therefore, they must be reduced or eliminated without losing relevant information in decision-making (T) (Wang et al., 2015). Therefore, a smaller set of decision conditions is preferred, assuming a loss of accuracy in the classification during the training phase. To calculate the importance of an attribute (a) (Equation 21), the effect it has on the classification must be analyzed if it ($a \in C$) is removed from the decision table (T):

$$\sigma_x(A, D)(a) = \frac{(\gamma(A, D) \leftrightarrow \gamma(A \leftrightarrow \{a\}, D))}{\gamma(A, D)} \quad (21)$$

This implies that if attribute (a) is not selected, it will cause an erroneous classification. Furthermore, this coefficient can be used with attribute set B , which is expressed as $\sigma_x(A, D)(B)$. In

this way, a subset can be selected from set B that most closely approximates attribute set A. The approximation error can then be calculated as (Equation 22):

$$\varepsilon(A, D)(B) = \frac{(\gamma(A, D) \leftrightarrow \gamma(B, D))}{\gamma(A, D)} \quad (22)$$

Regarding the reduction process indicated above, some authors such as Wang and Zhou (2009) proposed an algorithm that calculates the minimum subset generated from the total set of possible attributes. This is an iterative process in which different attributes are incorporated until the reduced subset S_{ij} that coincides with the decision set is reached (Equation 23).

$$S_{ij} = \{a \in c | a(X_i) \neq a(X_j)\} \quad (23)$$

Finally, the decision rules use a training matrix constructed from the information obtained from the conditional rules (IF) and their conclusions (THEN) (Figure 2). This matrix, called the discernibility matrix, presents those decision rules in which the analyzed information has not undergone any variation. Next, once the reduced set S_{ij} has been calculated, IF-THEN decision rules are generated.

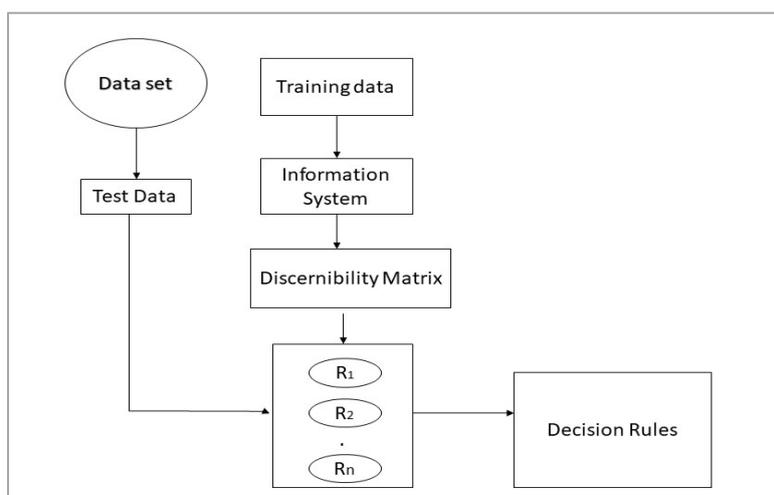


Figure 2. Decision rule diagram. *Source: Own elaboration.*

3.3. Support vector machine

The SVM model proposed in 1995 and subsequently developed by Cortes and Vapnik (Cortes et al., 1995; Vapnik et al., 1997) emerged as a machine learning alternative to neural networks and perceptrons (Rummelhart et al., 1986). The model is based on incorporating a series of variables (inputs) into a multidimensional space (Z) using a non-linear map. Thus, the problem is broken down into different dimensional spaces. The SVM model defines the maximum distance between the different classes or groups in Figure 3.

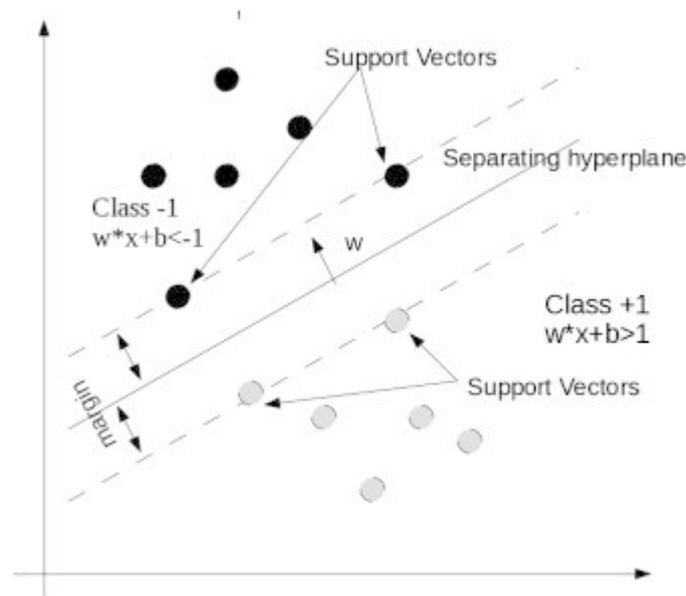


Figure 3. Separation of the problem into two dimensions. Source: (Zarogianni et al., 2013).

Therefore, solving the problem involves finding the separation of the data set in the hyperplane that generalizes as much as possible, obtaining an adequate solution. Given that the dimensions of the feature map can be very high in number, during the algorithm training process, solutions may be found that do not generalize adequately for all hyperplanes. To avoid this type of solution, the SVM model generates a model that is based on the training data, but which attempts to predict the target values, taking into account each of the associated features.

The model training and optimization process is initially based on the dataset that is composed, considering the different pairs of instances and labels (x_i, y_i) with $i=1 \dots n$, where x_i is a real number and $y_i \in \{-1, 1\}^n$ (Hsu et al, 2003). The popular SVM model (Equation 24) can be described as:

$$\min_{w, b, \varepsilon} \frac{1}{2} w^T w + C \sum_{i=1}^n \varepsilon_i \quad (24)$$

$$s. t \quad y_i (w^T \phi(x_i) + b) \geq 1 - \varepsilon_i \quad (25)$$

$$\varepsilon_i \geq 0 \quad (26)$$

The training vectors (x_i) are mapped in n -dimensional space using the ϕ function (Equation 25). The model adds a penalty parameter, $C > 0$, for the error term (ε_i) (Equation 26). It also adds an internal function (kernel) $K(x_i, x_j) = \phi(x_i)^T \phi(x_j)$ (Smola et al., 1998; Smola and Schölkopf, 2004). The major kernel functions commonly used in the SVM model are (Jiang et al., 2007):

- Linear $K(x_i, x_j) = x_i^T x_j$

- Polynomial $K(x_i, x_j) = (\gamma x_i^T x_j + r)^d, \gamma > 0$

- Radial basis function (RBF) $K(x_i, x_j) = \exp(-\gamma \|x_i - x_j\|^2)$, $\gamma > 0$

- Sigmoidal $K(x_i, x_j) = \tanh(\gamma x_i^T x_j + r)$

where γ , r and d are the kernel parameters of the function.

4. Results

In this section, we first describe the sample used from the automotive sector. Next, to enable stakeholders to analyze automotive companies while considering economic and financial variables and ESG ratings, we propose the creation of a multi-criteria ranking using GP, as described in the methodology section. Finally, a selection model (discretization) using rough sets is compared with the SVM model to determine whether the former methodology is more efficient for establishing a classification and distinction of groups based on financial variables.

4.1. Automotive sector database

For the purposes of this study, companies in the automotive sector worldwide are selected for inclusion, covering automotive vehicle manufacturers and auto parts components, classified under NACE Rev. 2 (2910) and NAICS Rev. 2 (3361) codes. The primary source of information is the Bloomberg platform (<https://www.bloomberg.com>). The sample comprises data from 2013 to 2024, with an initial number of 1,203 companies with available financial information. However, the number of observations is reduced to 430, as only those with complete ESG indicator data are included in the analysis.

Table 1. Descriptive statistics.

	ROA	ASSETS ROTATION	ROE	EPS
CV%	0.49	2.08	0.37	0.30
Mín	-40.65	0.00	-128.29	-33.69
Max	63.50	4.34	237.67	54.00
Mean	3.23	0.93	6.31	0.91
SD	6.56	0.45	17.14	3.03
	TOT. DEBTS/TOTAL			NON-CURRENT
	ASSETS	ASSETS/EQUITY	TOTAL LIABILITIES	LIABILITIES
CV%	1.58	1.82	0.19	0.17
Mín	0.00	1.00	0.35	0.00
Max	76.17	21.39	452641.97	249369.62
Mean	24.33	2.39	6265.00	2828.43
SD	15.44	1.31	32286.42	16371.35
	CURRENT LIABILITIES	NET DEBT	NET ASSETS	WACC
CV%	0.21	0.03	0.24	2.86
Mín	0.32	-60214.03	2.50	-3.85
Max	203272.35	113869.35	223386.15	33.43
Mean	3436.57	142.53	3496.11	11.89
SD	16359.56	4913.59	14739.46	4.15

Continued on next page

	CAPITAL STOCK	CAPITAL STOCK/TOTAL LIABILITIES	FINANCIAL LEVERAGE	FINANCIAL INTERESTS
CV%	0.24	0.21	1.23	0.24
Mín	2.50	4.00	1.00	0.00
Max	215909.58	607721.87	63.88	3341.93
Mean	3289.69	9674.45	2.65	36.23
SD	13857.08	45550.96	2.15	150.28
	TOTAL ASSETS	WORKING CAPITAL	EBIT	EBITDA
CV%	0.52	0.24	0.21	0.22
Mín	14.80	-22985.08	-4518.52	-1476.82
Max	610903.39	45057.51	26678.54	54250.50
Mean	22786.21	777.79	364.22	740.34
SD	43979.62	3243.61	1749.35	3432.02
	COMPANY VALUE	PER	CAPEX	INCOME
CV%	0.18	0.43	0.20	0.25
Mín	-2727.87	0.01	-33731.21	0.00
Max	1053847.01	576.64	0.00	296008.61
Mean	4818.20	13.41	-376.79	6477.76
SD	26836.32	31.08	1913.65	25849.22
	CASH AND OTHER	ESG		
CV%	0.22	0.68		
Mín	0.00	0.00		
Max	84226.69	6.57		
Media	1307.77	1.15		
SD	5880.30	1.68		

Source: Own elaboration.

The construction of the multi-criteria ranking has involved the selection of economic and financial variables of the companies, as well as ESG scores. Table 1 shows the selected variables with their descriptive statistics.

It is important to emphasize the significant variability in the variables, which may be due to factors such as differences in company size, regulatory changes, supply chain issues, and variations in demand.

4.2. Multicriteria ranking: Goal programming

As stated, the creation of a multicriteria ranking facilitates stakeholders in the analysis of variables and dimensions in a combined and concurrent manner. This approach enhances the accuracy of decision-making, as it eliminates the potential biases that can arise from analyzing multiple rankings with a single variable. In this section, we apply the GP methodology mentioned in the methodology section to create a multi-criteria ranking in the automotive sector, considering not only financial variables but also ESG scores and criteria.

As outlined in the methodology, the EGP model introduces a control parameter λ , which enables the decision-maker to explore two opposing optimization models. Therefore, parameter λ is crucial,

since its value between 0 and 1 modify the weightings of the criteria and, consequently, the final classification. Thus, the WGP approach ($\lambda=1$) reveals a consensus solution that minimizes the sum of all deviations and the MINMAX approach ($\lambda=0$), which focuses on minimizing the most discordant or maximum deviation. To mitigate the subjectivity associated with selecting a single “optimal” value of λ , a comprehensive sensitivity analysis is performed. The procedure consists of generating 500 uniformly spaced values across the continuous binary interval (0,1). Rather than employing random sampling from a probability distribution, this approach applies a deterministic discretization of the parameter space (e.g., $\lambda = \{0, 0.001, 0.004, \dots, 1\}$). This design ensures that the full spectrum of possible weight configurations, from the fully compensatory WGP model to strictly non-compensatory MINMAX model, is systematically represented in the analysis.

Unlike traditional optimization techniques that aim to identify a single global maximum, this methodology does not determine a unique optimal λ based on goodness-of-fit measures. Instead, optimality is conceptualized in terms of robustness. By computing rankings across all 500 simulated instances, the analysis identifies companies that are consistently strong, regardless of the weighting scheme.

In Figure 4, according to these median values, three groups of variables can be identified. The first group has variables weighted between 30% and 40% (net assets and sales). The second group includes variables weighted between 5% and 10% (market capitalization and finished products). Finally, the third group includes the rest of the variables with weightings of less than 5%.

However, it is important to note that even if the weighting of a variable is considered low, this does not necessarily mean that its relative importance in calculating the company’s final performance (construction of the multicriteria ranking) is also low. This is due to the high correlation that may exist between many of the criteria. Therefore, a low weighting in one criterion may result in a higher weighting in another highly correlated criterion. Conversely, low weightings may be indicative of a lower dispersion in the values of a criterion. In this instance, it is not possible to adequately differentiate the companies. As we discuss later, it is necessary to use a methodology that enables some degree of discrimination. Examples of such methodologies include the SVM and the rough set model that has been proposed. Nevertheless, the merits of GP are evident in its ability to simultaneously analyze criteria and eliminate the need for a panel of experts to weigh each criterion.

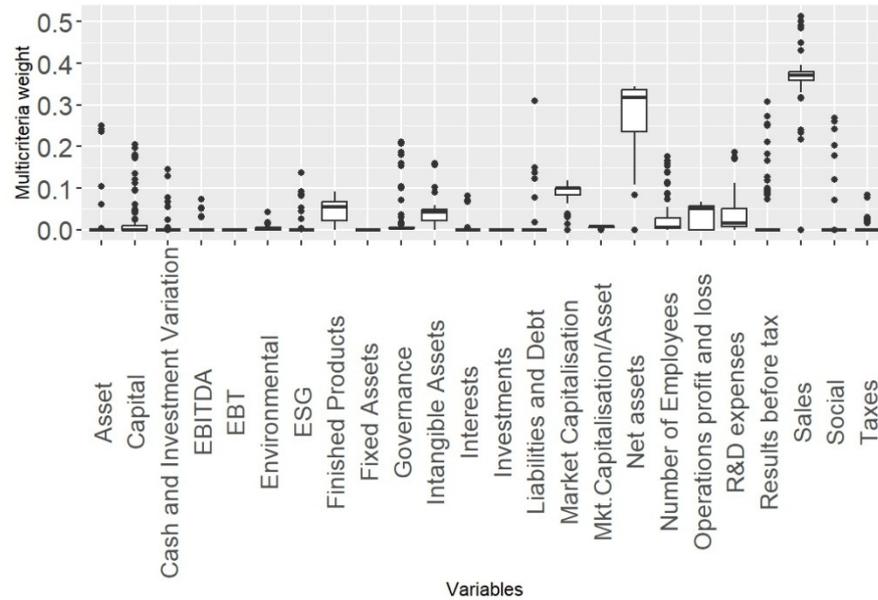


Figure 4. Weights assigned to each criterion for different λ . *Source: Own elaboration.*

On the other hand, it is interesting to analyze the trade-off between ESG versus financial criteria. This is how ESG criteria change in relation to other criteria depending on the value of λ . The simulation reveals a distinct trade-off in those metrics. As shown Figure 5, parameter λ functions as a control variable that balances or transitions between these two dimensions. There is a dominance of ESG criteria with λ values between 0.25 and 1. As the value of λ increases and approaches 1, the model places greater emphasis on consensus indicators, those that exhibit strong alignment with the overall patterns observed in the dataset. In our case, ESG criteria dominate the weighting in this range, suggesting that sustainability metrics are consistent and positively correlated across the sector. On the other hand, financial criteria dominate with λ values below 0.25. In this case, as λ approaches 0, the MINMAX solution model emphasises the treatment of discordant indicators to minimize the maximum deviation. In this range, financial variables increase significantly in weight. This implies that financial performance in the automotive sector is more heterogeneous and more susceptible to outliers than ESG performance.

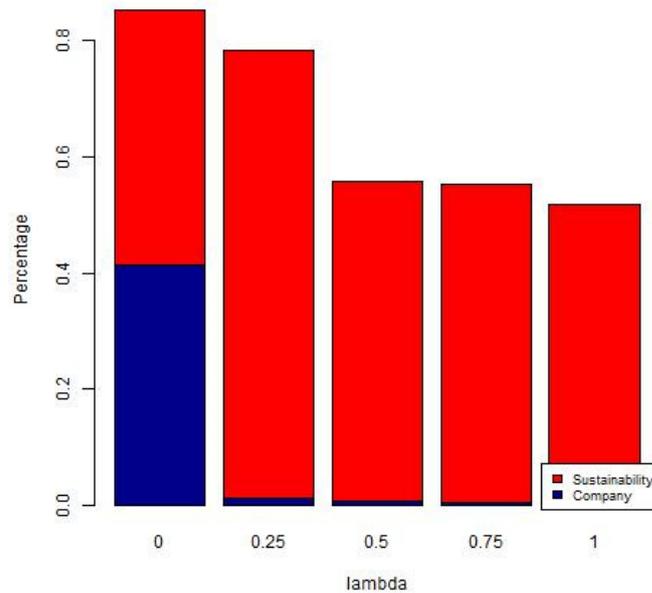


Figure 5. Weights assigned to ESG criteria versus other criteria for selected λ values.

Source: Own elaboration.

As stated, depending on the values of λ , the weights of the different criteria are modified, which could also affect the ranking. For the final consensus ranking (Figure 6), the median position achieved by each company across the 500 simulations is employed. The median-based approach mitigates the influence of extreme fluctuations associated with specific λ values, yielding a stable and representative indicator of each company's overall performance. In this ranking, companies have been ordered according to their median position for the simulated values of λ . Therefore, an increase in multi-criteria score indicates an improvement in the ranking. In this instance, Toyota and Volkswagen are notable exceptions. Mercedes-Benz Group AG and Bayerische Motoren Werke AG are in an intermediate position with a score of 0.5 out of 1. Finally, the rest of the companies have scores below 0.25.

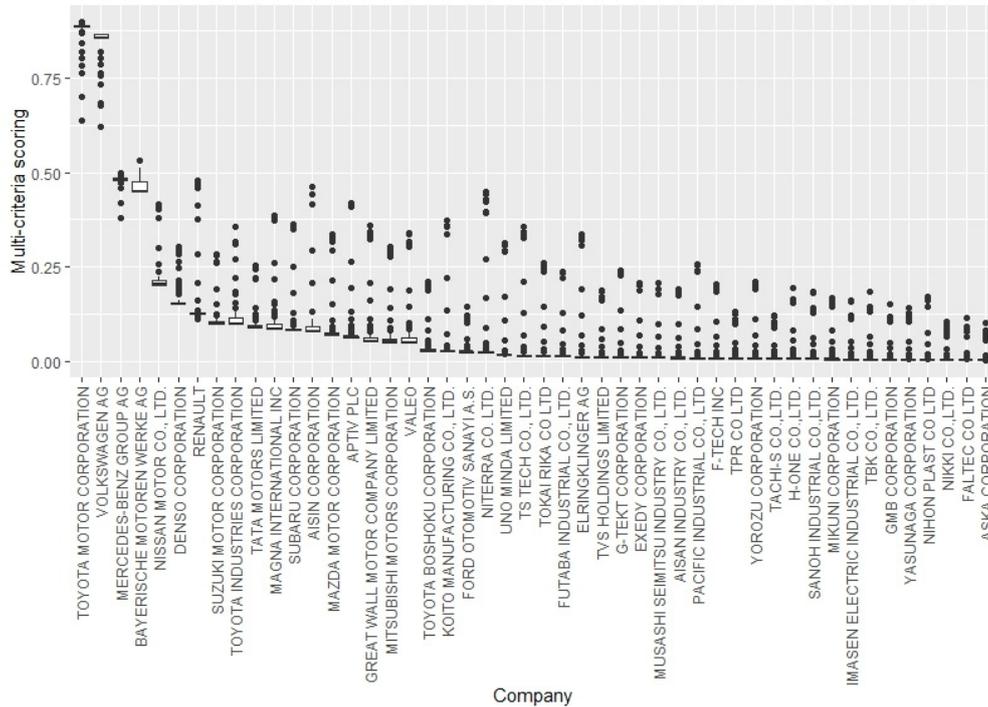


Figure 6. Multi-criteria ranking of automotive companies. *Source: Own elaboration.*

It is possible to analyze how different values of λ affect the variability of the multicriteria score and, therefore, the ranking. Thus, based on the previous figure (Figure 6), this effect can be included (Figure 7). We can see that the variance in a company's ranking across the 500 simulations serves as a proxy for its balanced performance. As can be seen, the ranking varies depending on the value of λ , although there are some exceptions. For example, the top two positions in the ranking would remain the same. It is noteworthy in these two cases that the highest scores for the first two companies are obtained with λ values greater than 0.25. It should be noted that weights exceeding this threshold indicate that ESG criteria take precedence over financial considerations (Figure 5). For the remaining companies, higher scores are achieved in the ranking when the λ values are less than 0.25. In other words, there are some companies that present low variance (e.g., the top performers like Toyota and Volkswagen) have Pareto optimal behavior, performing strongly in financial and ESG dimensions. It could be said that their position in the rank is independent of the weight assignment strategy. On the other hand, there are some companies that present high variance with volatile rankings position. These companies may perform strongly in financial dimensions but weaker in ESG aspects or vice versa, leading their ranking to fluctuate (either declining or improving) depending on whether the model (λ) emphasizes consensus or discordance.

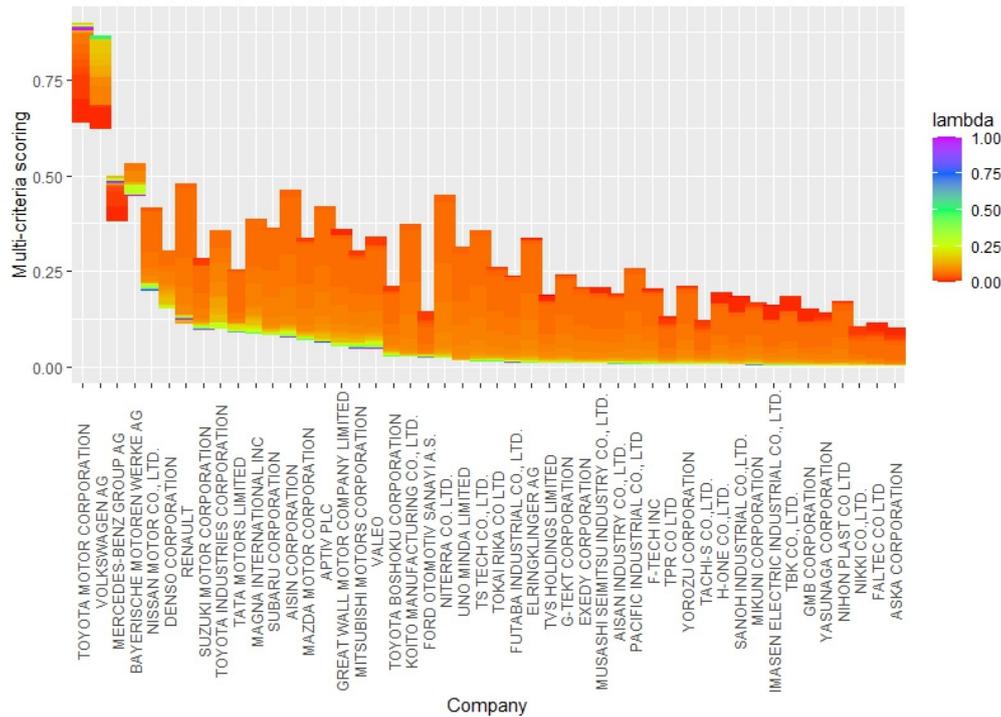


Figure 7. Weights assigned to ESG criteria versus other criteria for selected λ values.
Source: Own elaboration.

4.3. ESG discriminant analysis in automotive companies: Rough sets

In the preceding section, a multi-criteria ranking is developed. As mentioned, most companies are within the same range of the ranking. This complicates the process of segmenting companies based on ESG data. To this end, an analysis is carried out using the rough sets methodology to determine whether it is possible to discriminate between the ESG ranges of companies based on economic and financial data. In some cases, these ranges may be relatively close, leading to indistinguishability. In summary, the available data do not enable sufficient analysis to determine whether a company belongs to one group or another.

First, the companies in the sample have been classified into three groups based on their overall ESG score, as outlined below: Companies with an ESG score below 3 are included in group 1; those with an ESG score between 3 and 4, inclusive, are included in group 2; and companies with a score above 4 are included in group 3. It is true that many statistical studies provide examples of groups created based on sample quartiles or using clustering algorithms. However, in this study, we opt to create three groups, as is common in studies related to the automotive sector (Tortato et al., 2010; Kamble et al., 2021). This also enables more even distribution. In this case, group 1 represents 37,5% of the sample; group 2 represents 29,17% of the total sample; and, group 3 represents 33,33% of the sample.

As illustrated in Figure 8, the box plot graph displays the three groups in the sample. It is important to note that, for group 2, the sample shows slightly less dispersion than the other groups. This could present a challenge when using discriminant analysis with methodologies such as SVMs, which require a sample to be as balanced as possible. Should one opt to use the rough sets methodology, it would not be necessary to have a balanced sample.

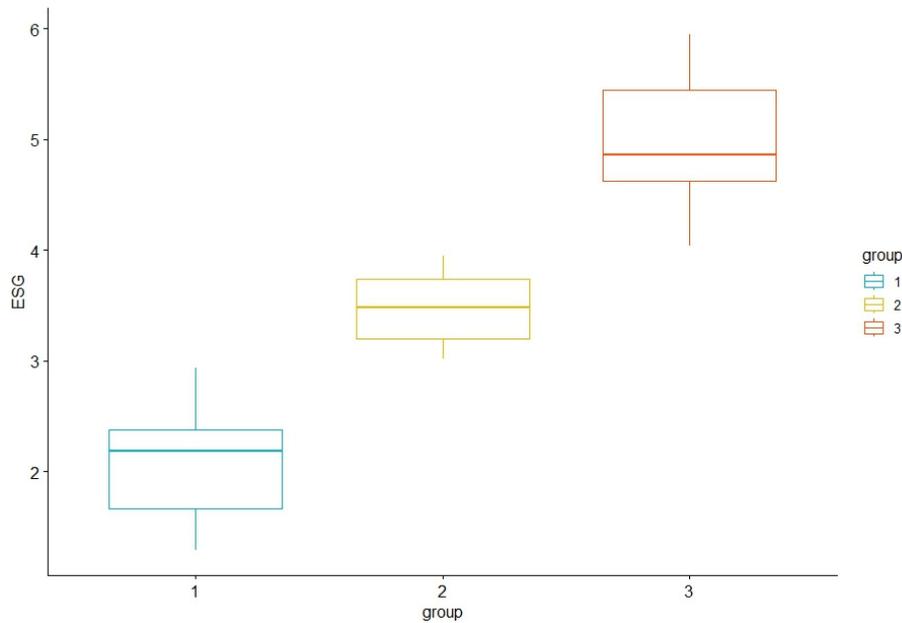


Figure 8. Boxplot ESG value by group. *Source: Own elaboration.*

Table 2 shows the cross-correlations between the variables; in this case, with significant probabilities of 95% and 99%. Of particular interest is the relationship between companies' economic and financial variables and their ESG rating. First, it should be noted that the only non-significant correlation with the ESG rating would be the Market Capitalization/Assets ratio. All the others have proved to be significant. Most of these indicators demonstrate a strongly positive correlation, including assets, liabilities, sales, and EBITDA. Conversely, the variables Employees and Investment in R&D exhibit the least correlation with the ESG rating. It is evident that company size is highly positively correlated with the ESG score. This finding aligns with studies cited in the relevant literature (Charlo et al., 2017).

The high correlation between many of the financial variables could suggest the existence of multicollinearity between the variables. However, it should be noted that this does not present a significant problem in the application of the proposed methodologies, the GP model and the rough set model.

On the one hand, multicollinearity does not affect the weightings in GP because it minimizes deviations from multiple goals through an objective function that incorporates positive and negative deviation variables. The weightings in the objective function, as in WGP, are assigned a priori to prioritize objectives. Multicollinearity in financial variables (e.g., correlated ratios such as liquidity and capitalization) could affect their feasibility, but it does not alter the weights, as these do not depend on statistical correlations. In contrast, in regression, multicollinearity violates assumptions such as predictor independence, leading to unreliable coefficients. This makes GP robust for financial applications, where variables such as liquidity ratios or debt ratios are often correlated, without compromising user-defined priorities. For example, when GP is used to estimate regression-like parameters, such as Least Absolute Value (LAV) regression, it is less sensitive to multicollinearity than ordinary least squares. The GP model therefore enables correlated variables to be incorporated without the need to eliminate them (García et al., 2013; Pérez-Gladish et al., 2007).

Table 2. Correlation matrix.

	Asset	Investm ents	Net assets	Liabil ity	Sales	R&D	Ebitd a	Mkt. Cap/As sets	Emplo yees	Auto part	ESG
Asset	1.000	0.843**	0.985 **	0.991 **	0.986 **	0.693 **	0.985 **	0.136	0.742**	-0.69 1**	0.839 **
Investm ents	0.843 **	1.000	0.873 **	0.804 **	0.815 **	0.562 **	0.815 **	0.185	0.598**	-0.47 7**	0.737 **
Net assets	0.985 **	0.873**	1.000	0.954 **	0.969 **	0.670 **	0.972 **	0.187	0.723**	-0.62 2**	0.865 **
Liability	0.991 **	0.804**	0.954 **	1.000	0.979 **	0.703 **	0.975 **	0.085	0.747**	-0.72 5**	0.802 **
Sales	0.986 **	0.815**	0.969 **	0.979 **	1.000	0.652 **	0.980 **	0.175	0.712**	-0.67 9**	0.817 **
R&D	0.693 **	0.562**	0.670 **	0.703 **	0.652 **	1.000	0.670 **	-0.158	0.904**	-0.56 0**	0.491 **
Ebitda	0.985 **	0.815**	0.972 **	0.975 **	0.980 **	0.670 **	1.000	0.216	0.722**	-0.67 0**	0.851 **
Mkt. Cap/Ass ets	0.136	0.185	0.187	0.085	0.175	-0.15 8	0.216	1.000	-0.034	0.005	0.276
Employ ees	0.742 **	0.598**	0.723 **	0.747 **	0.712 **	0.904 **	0.722 **	-0.034	1.000	-0.44 4**	0.517 *
Auto part	-0.69 1**	-0.477* *	-0.62 2**	-0.72 5**	-0.67 9**	-0.56 0**	-0.67 0**	0.005	-0.444 **	1.000	-0.46 4**
ESG	0.839 **	0.737**	0.865 **	0.802 **	0.817 **	0.491 **	0.851 **	0.276	0.517**	-0.46 4**	1.000

* Significant to 5% ($p < 0.05$) and ** significant to 1% ($p < 0.01$). Source: Own elaboration.

On the other hand, in the case of the rough set model, multicollinearity does not directly affect the “weightings” since these do not exist as estimated coefficients. There are only IF-THEN decision rules without estimating numerical weightings dependent on correlations. The importance of the attributes of the variables is created from attribute reduction, which eliminates redundancies without assuming linear independence. Thus, while in a multiple linear regression model, in the presence of multicollinearity, the variance inflation factors (VIF) increase, reducing the reliability of coefficients in the rough set model, and the use of approximations (lower/upper) focuses on the analysis of uncertainty and discernibility (D’Amato, 2007).

To apply the rough set methodology, it is necessary to select variables that maintain a significant correlation with the ESG value. These variables are used to create an information system that characterizes the ESG classification, dividing it into the three groups mentioned above. This information system represents the attributes of the variables that make up the condition (IF), while a second group of attributes represents the decisions or response variable (THEN) for a company to be included in one or another classification group. As outlined in the methodology section, these two

groups constitute a series of disjoint sets. This results in a substantial number of decision rules, and, therefore, a process of reduction is necessary, without significant loss of information. Table 3 shows an example of four decision rules belonging to the discretization matrix.

Table 3. Example of the discretization matrix.

	1	2	3	4
Asset	[17.1, Inf]	[-Inf, 15.2]	[-Inf, 15.2)	[17.1, Inf]
Investments	[13,4, Inf]	[-Inf, 13.4)	[-Inf, 13.4)	[13,4, Inf]
Net assets	[14, Inf]	[-Inf, 14]	[-Inf, 14)	[14, Inf]
Liability	[13.7, Inf]	[-Inf, 13.7)	[-Inf, 13.7)	[13.7, Inf]
Sales	[-Inf, Inf]	[-Inf, Inf]	[-Inf, Inf]	[-Inf, Inf]
R&D	[9.41e+05, Inf]	[-Inf, 1.59e+04)	[1.59e+04, 9.41e+05]	[9.41e+05, Inf]
Ebitda	[11, Inf]	[-Inf, 11)	[-Inf, 11)	[11, Inf]
Employees	[9.66e+04, Inf]	[-Inf, 9.66e+04)	[-Inf, 9.66e+04)	[9.66e+04, Inf]
Auto part	[-Inf, 0.5)	[0.5, Inf]	[0.5, Inf]	[0.5, Inf]
ESG	1	4	4	1

Source: own elaboration.

This matrix generates a range of values for each of the variables and observations, based on the relationships with the decision variable, which, in this case, is the ESG score for each company. As mentioned, the discretization matrix reduces the computational burden of the decision rules without significantly compromising the integrity of the information for the attribute sets.

A total of 80% of the sample is used to construct and estimate the model, while the remaining 20% is used to test the results. The selection of the sample is carried out at random. A total of one thousand simulations are carried out to ensure the reliability of the results, which could not be dependent on the selection of a sample. In order to ascertain the validity of the proposed rough set model in adequately estimating, discriminating and grouping companies at different ESG levels based on their economic and financial data, a comparison is made with the SVM model. To do this, the same sample is used, with the same variables, and the sample selection simulation (80/20 split) is performed. The parameters used in the model estimation are: Kernel (radial), regularization parameter or cost 1, and gamma 0.1). Table 4 presents the results of both models.

Table 4. Percentage of accuracy for rough set and support vector machine (SVM) models.

Overall Accuracy	Rough set			SVM		
	Precision	Recall	F1 score	Precision	Recall	F1 score
Group						
1	1	1	1.0000	0.9796	0.8176	0.8913
2	0.8	1	0.8888	0.6018	0.6795	0.6382
3	1	0.75	0.8571	0.8177	0.8826	0.8489

Source: Own elaboration.

As shown in Table 4, the rough set model has a much higher overall accuracy than the classic SVM model. The SVM model attempts to draw a “dividing line” (hyperplane) between groups. If a company, for example, has “high assets” but “low ESG”, the model could have difficulties if it is close to the boundary. However, the rough set model takes into account that there are companies that may be indistinguishable; i.e., they may have similar values for some financial variables but different ESG scores. Thanks to the lower and upper approximations made by the model, a boundary zone is created that enables it to classify companies more accurately than the rigid boundaries of the SVM model. Therefore, the proposed rough set model can be a good starting point for classifying and grouping automotive companies into ESG levels based on financial variables. Furthermore, it suggests that the relationship between financial variables and ESG ratings is based on non-linear rules.

It is interesting to analyze the behavior in detail for each of the groups considered. In the case of the first group, the low ESG group, the rough set model achieves high precision and high recall, indicating that the ESG level is correctly identified based on financial variables with few or no false positives. The robustness for this group, measured by the F1 score, is equally high. For the group with average ESG values, the accuracy is high, although somewhat lower than in the previous group, and the robustness is reduced. For the last group, the high ESG group, although the accuracy is very high, both the recall and the F1 score decrease, meaning that there are companies with a high ESG level that the model is unable to determine. For all groups and metrics, the rough set model outperforms the SVM model.

It can be concluded that the rough set theory model produces transparent, interpretable if-then decision rules. These rule-based results enable automotive executives to identify the financial thresholds their companies must meet to be recognized as ESG leaders in the market.

5. Discussion and conclusions

In this study, we present an alternative approach for constructing a multi-criteria ranking applied to the automotive sector. This type of ranking has the advantage of analyzing multiple dimensions, in contrast to those that analyze only a single dimension. Multi-criteria rankings enable analysts to compare companies by taking all variables into account simultaneously, including financial variables and ESG scores.

Conversely, the rough set methodology has enabled the classification of companies into different categories based on their ESG level. In order to verify the effectiveness of this methodology, a comparison was made with the classic classification model, such as the SVM. In order to circumvent any potential issues with the results, a simulation of 1,000 iterations was conducted in the sample selection process for the estimation of the models, namely the rough set and the SVM. It was verified that the rough set model can be an alternative to the SVM model in the ESG classification of companies based on financial variables.

Although we present a robust and innovative framework for assessing the integrated financial and sustainability performance of automotive companies, several limitations must be acknowledged for future research.

The most significant limitation concerns the reliance on a single data provider for sustainability metrics: Bloomberg’s ESG score. As an aggregate indicator combining numerous environmental, social, and governance dimensions, it functions to some extent as a “black box”. In future studies, researchers could break down this composite measure to identify which

components most influence the multi-criteria ranking results. The use of other types of databases that offer ESG scores could also be considered to determine whether there would be any variation in the ranking constructed using the Bloomberg database.

It is also important to note the limitations inherent in the methodological approach of the study. While the multi-criteria classification framework reduces reliance on external expert judgement compared to other assessment techniques, expert input is necessary during the initial variable selection phase. The adoption of neural network-based tools could automate and refine this step by identifying relevant variables through data-driven feature selection. Furthermore, although the rough set theory model outperformed the SVM model in terms of classification accuracy, its efficiency may decline when applied to qualitative or mixed-type variables. Bootstrapping may be interesting when comparing these models instead of a 80/20 split sample. Furthermore, the use of dimensionality reduction tools (PCA) may be of interest. Comparative analyses between rough set and neural network models, capable of capturing more complex and non-linear relationships between variables, represent an interesting direction for future research.

Author contributions

Fernando García: Methodology, Formal Analysis, Writing: original draft, review and editing
 María del Carmen García: Conceptualization, Formal Analysis, Validation, review.
 Sorely García: Conceptualization, Investigation, Data Curation. Writing: original draft
 Javier Oliver: Conceptualization, Methodology, Investigation, Software.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

Conflict of interest

The authors declare no conflicts of interest.

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