mathematics

Article

A Multicriteria Customer Classification Method in Supply Chain Management

Felipe Barrera [1], Marina Segura [2,*] and Concepción Maroto [3]

[1] Santalucía Chair of Analytics for Education, Universidad Pontificia Comillas, Calle de Alberto Aguilera, 23, 28015 Madrid, Spain; fbarrera@comillas.edu
[2] Department of Financial and Actuarial Economics & Statistics, Universidad Complutense de Madrid, 28223 Madrid, Spain
[3] Department of Applied Statistics and Operational Research and Quality, Universitat Politècnica de València, 46022 Valencia, Spain; cmaroto@eio.upv.es
* Correspondence: marina.segura@ucm.es

Abstract: Since Kraljic's strategic matrix was applied to supply chain management, classification of items, suppliers, and customers has become of increasing interest to research and companies. The aim of this research is to develop an easily interpretable multicriteria classification matrix method and validate it in real-world scenarios with a robustness analysis. This method assigns alternatives to one of four classes defined by critical dimensions that integrate several evaluation criteria. Initially, a global search pre-classifies the alternatives using the PROMETHEE net flows. Then, two local searches are carried out that make use of the discriminant properties of the net flow signs to improve the quality of the assignments. This approach is specifically applied to pre-classified alternatives near the boundary between two or more categories. The method has been validated by segmenting thousands of customers. Four customer segments were identified: strategic, collaborative, transactional, and non-preferred. A comparison was made between the results and those derived from an alternative method. Through an extensive sensitivity analysis, the proposed method was shown to be robust to parameter variation, highlighting its reliability in real dynamic contexts. The method provides valuable, easily interpretable information, which constitutes the basis for developing personalised strategies to enhance customer relationship management.

Keywords: multiple criteria analysis; matrix classification algorithm; supply chain management; customer segmentation; RFM dimension; MCDM; GLNF; PROMETHEE

MSC: 90B06; 90B50; 90C29; 91B16

Citation: Barrera, F.; Segura, M.; Maroto, C. A Multicriteria Customer Classification Method in Supply Chain Management. *Mathematics* **2024**, *12*, 3427. https://doi.org/10.3390/math12213427

Academic Editors: James Liou and Artūras Kaklauskas

Received: 6 October 2024
Revised: 29 October 2024
Accepted: 30 October 2024
Published: 31 October 2024

1. Introduction

Globalisation has intensified competition, motivating organisations to optimise their processes and improve Supply Chain Management (SCM) to effectively respond to customer needs, considering times of crisis where agility and resilience are crucial [1]. Multiple-criteria decision-making (MCDM) is a crucial field in decision science that aims to select the most suitable option from several alternatives, considering multiple potentially conflicting criteria and reflecting the preferences of decision-makers (DMs) [2]. MCDM has been effectively applied in SCM, such as, financial [3], supplier selection [4], information technology industry [5], and business analytics [6].

One of the challenges in SCM is the segmentation of suppliers and customers, particularly in cases where no set of alternatives have been pre-assigned to categories. While multicriteria techniques are often employed to address supplier segmentation problems [7], their application in customer segmentation is less widespread, with clustering techniques, such as K-means, often employed instead [8]. Some hybrid models integrate multicriteria techniques to determine criteria weights or model customer preferences [9–12].

In multicriteria decision-making, problems such as choice, ranking, classification, and sorting are addressed [2,7]. Sorting groups alternatives into an ordinal set of predefined categories based on multiple criteria [13]. Segura and Maroto [14] provide some examples of supplier classification. On the other hand, Barrera et al. [8] addressed sustainable customer sorting. There is also interest in solving sustainable supplier evaluation (e.g., [15]).

There has been a great deal of interest in the application and development of multicriteria sorting methods [7]. Recently, Barrera et al. [16] introduced the Global Local Net Flow Sorting (GLNF sorting) method, which has been applied in supplier segmentation and subsequently implemented by Barrera et al. [8] in customer segmentation. This approach discriminates between alternatives based on the preference properties of the net flows of the outranking method of Preference Ranking Organisation METHod for Enrichment Evaluation (PROMETHEE).

Compared to sorting methods, the literature on multicriteria classification methods is limited. Nevertheless, in recent years, there has been a growing significance attached to classification issues, especially within the realm of strategic organisational management. This increasing interest stands as a potential response to the need to generate more flexible and adaptive classifications in strategic and managerial scenarios, where group homogeneity and patterns are not constrained by a preferential order. For example, applying marketing strategies aimed at different customer segments, all of which are considered interesting to the company, without establishing a preferential order.

In practice, in both multicriteria classification and sorting methods, alternatives close to group boundaries require detailed analysis. This is due to the difficulty of understanding that suppliers or customers with similar performance are assigned into groups with very different business strategies. Therefore, the development of algorithms to automate this analysis would allow for multicriteria techniques to be applied in contexts with thousands of alternatives.

The objectives of this research are, firstly, to develop a robust and easy-to-interpret method for solving classification problems in an MCDM context. This method, called GLNF matrix classification, assigns alternatives to one of four groups defined by critical dimensions according to the preferences of the company, thereby integrating several evaluation criteria into a classification matrix. Secondly, to validate this method in an empirical case of customer segmentation. Thirdly, to provide an open access implementation of the new algorithm in R language.

The algorithm is based on the discriminant properties of the net flow of the PROMETHEE method, as well as on the concepts of global search and local search introduced by Barrera et al. [16]. The aim is to integrate these search and discrimination concepts with segmentation based on critical dimensions such as the Kraljic matrix approach, a tool renowned for its simplicity and effectiveness in the visual segmentation.

This method starts with the definition of the two relevant dimensions. A pre-classification is then carried out by a global search, assigning the alternatives to one of the four quadrants according to their net flow value. This is followed by two local searches, subdividing the dimensions with the aim of improving the allocation of alternatives close to the boundary of two groups by identifying the most appropriate group.

Validation has been carried out using real data on 8157 customers in a Business-to-Business (B2B) model. The evaluation criteria are used to construct two main dimensions: the first, widely known in the literature as RFM, incorporates recency, frequency, and monetary criteria, providing a detailed view of customer-buying performance [17]. The second dimension, called customer collaboration (CC), is based on the following criteria: quota compliance, variety of products, and sustainable commitment, the latter being broken down into reverse logistics and shared information and used to foster supply chain integration [8,18]. The results obtained are compared to those generated with the PROMETHEE-based method used by Casas-Rosal et al. [19] and Segura and Maroto [14].

The main contributions of this research include, firstly, extending the implementation of the net flow properties from PROMETHEE and the concepts of local and global search to design a robust method to classify alternatives in a two-dimensional matrix that is easy to interpret graphically. Secondly, the method has been implemented using the R programming language and validated in an empirical case involving the segmentation of thousands of customers. In addition, an extensive sensitivity analysis has shown little change in customer allocation in response to parameter variations. Therefore, it is a robust and easy-to-interpret method that can be integrated into Decision Support Systems (DSS) to facilitate the implementation of personalised customer strategies and policies.

The remainder of this paper is structured as follows: In the second Section, a review of the literature on multicriteria classification methods is presented. Section 3 explains the methodology of the PROMETHEE method. Section 4 explains in detail each of the steps of the proposed classification algorithm, followed by an empirical case to validate the method. Section 5 presents the results obtained, together with their comparison with an alternative method, and the sensitivity analysis. Finally, discussion and conclusions are presented in Sections 6 and 7, respectively.

2. Literature Review

Multicriteria methods can be categorised into full aggregation, outranking, goal, aspiration or reference-level, multi-objective mathematical programming, and non-classical MCDM approaches [2]. This paper focuses on the outranking-approach category, specifically on the PROMETHEE-based methods.

The classification/sorting problems in MCDM begin by evaluating alternatives based on multiple criteria to assign them to k predefined groups $C_1, C_2 \ldots, C_K$. In classification, the groups are not defined ordinally, while in sorting, a descending preferential order is considered, where C_1 is the most preferred and C_k the least preferred. Chen et al. [20] categorise classification types into four, based on whether it is a complete classification with overlapping alternatives. Type 1 offers a complete classification where each alternative is assigned to a single group. In Type 2, there is a complete classification of alternatives, and one alternative can belong to more than one group. In Type 3, an incomplete classification of alternatives is observed, where the assigned alternatives can belong to a single group. Finally, in Type 4, an incomplete classification of alternatives is found, where the classified alternatives can belong to more than one group.

To address two-dimensional classification challenges, Kraljic's model employs profit impact and supply risk to represent item segmentation and analyse the purchasing portfolio. Managers have applied a similar approach for supplier and customer segmentation based on their main characteristics, generating a matrix with four areas, as well as recommendations and best actions for each group [21–23]. Segura and Maroto [14] and Casas-Rosal et al. [19] propose a classification method based on PROMETHEE net flows to assign suppliers and customers into four quadrants formed by two multicriteria dimensions, which in this research is designated as the global search. In the first two approaches, there is a also comparison with the Multi-Attribute Utility Theory (MAUT) method.

On the other hand, the NexClass method, proposed by Rigopoulos et al. [24], is grounded in the outranking approach and assigns alternatives by assessing the degree of non-exclusivity for inclusion or not in a category using the concept of category entrance threshold. Other methods based on the outranking concept can also be found in the literature [25,26].

Ghanbarizadeh et al. [27] proposed a hybrid model to obtain a matrix with bidimensional MCDM classifications that considers relationships among criteria. Specifically, these authors apply the VIekriterijumsko Kompromisno Rangiranje (VIKOR) to segment the items of a construction project according to the dimensions of supply risk and purchasing importance. Tchangani [28] presents the fuzzy method, where the assignments are made by calculating the classifiability indices and the rejectability index. Liu et al. [29] introduce a multiple-criteria Bayesian hierarchical model for analysing heterogeneous consumer preferences in order to create segments.

A literature review was conducted to identify multicriteria classification methods for SCM. The summarised results, including the characteristics of the method and its application, are presented in Table 1. Notably, a substantial portion of these methods adopt a conceptual framework based on outranking principles. In the context of customer segmentation, two empirical application cases are observed: the classification of food consumers [19] and the classification of retailers utilising banking services, initially described by Rigopoulos et al. [30] and subsequently replicated by in other research articles. Most methods have not been validated with a number of alternatives exceeding 30, with the highest recorded at 548 by Casas-Rosal et al. [19]. Furthermore, the average number of criteria employed in these applications is 10, while the average number of categories considered is four.

Table 1. Multicriteria classification methods.

Article	Method/Framework	Application Area	Alternatives	Criteria	Groups
Casas-Rosal et al. [19]	Outranking: PROMETHEE	Food B2C Customer segmentation	548	10	4
Rigopoulos and Karadimas [31]	NexClass/Outranking: non-exclusivity	Human resource management	20	5	2
Ghanbarizadeh et al. [27]	Goal reference-level: VIKOR	Purchasing portfolio	28	11	4
Tchangani [28]	BFNC/Bipolar analysis: classifiability and rejectability	Country risk	209	6	3
Segura et al. [15]	Outranking: PROMETHEE; Full aggregation: MAUT	Supplier segmentation	6	7	4
Gomez Famá and Alencar [32]	NexClass/Outranking: non-exclusivity	Human resource management	5	16	5
Segura and Maroto [14]	Outranking: PROMETHEE; Full aggregation: MAUT	Supplier segmentation	67	7	4
Rigopoulos et al. [24]	NexClass/Outranking; non-exclusivity	Banking B2B Customer segmentation	20–500	13	4
Tchangani [33]	Satisficing Game Theory; selectability and rejectability	Banking B2B Customer segmentation	20	13	4
Rigopoulos et al. [30]	NexClass/Outranking: fuzzy inclusion degrees	Banking B2B Customer segmentation	20	13	4
Chen et al. [20]	Additive value function: SMART (Simple Multi-Attribute Rating Technique)	Water resources planning	10	7	3

On the other hand, the methods focused on sorting have had greater development and application in the literature, highlighting the outranking approach methods, particularly those based on PROMETHEE, which are the most representative [7,34]. The most widely cited outranking method is PROMSORT [35], which is based on PROMETHEE. Other novel methods based on PROMETHEE include GLNF sorting [16], β-PROMETHEE [36], and FlowSort [37].

GLNF sorting has been used in supplier and customer segmentation [8,15]. In contrast to PROMSORT, it has the ability to classify all alternatives without requiring the definition of an additional parameter. Another distinction of this method with respect to others presented in the literature is that; although, like methods such as FlowSort and PROMSORT, it uses limiting profiles to obtain a classification, which in GLNF sorting, corresponds to a pre-classification, since it is subsequently refined by two local searches that use the comparison between alternatives to discriminate them according to their preference values. However, the application of the concepts of net-flow-based searches used in GLNF sorting have only been used in the context of obtaining ordered groups.

In summary, the literature review indicates that there is limited development of multicriteria classification methods, most of which have not been validated with a large number of alternatives, especially in the realm of customer segmentation in B2B models (e.g., [24,30,33]). While there are different types of classification methods, the choice will depend on the characteristics of each case. For example, in a comprehensive customer portfolio management to contribute positively to sustainable customer relationship management (CRM) practices, it is essential to consider complete classifications that often involve a large number of customers. Furthermore, in situations where resource use is limited (e.g., targeted marketing) or to facilitate decision-making in contexts of large volumes of data, the use of Type 1 classification methods may be more appropriate than the other types identified in the literature (e.g., [24,30,32,33]). On the other hand, the methods found in the literature that address two-dimensional MCDM classification problems do not consider the issue of uncertainty: that some alternatives may lie on the borderline between two or more categories (e.g., [14,19,24,27,31]). Finally, some graphical representations, highly valued by DMs, are not considered in certain methods (e.g., [20]).

Considering the deficiencies mentioned in the previous paragraph, this research addresses gaps in the existing literature by developing a robust and easily interpretable multicriteria classification method. The approach includes a comprehensive analysis of alternatives located between category boundaries. To facilitate the implementation of this method in scenarios with a large number of alternatives within a DSS, a corresponding function has been proposed in the R programming language. Specifically, the method extends the use of global and local search concepts, previously employed in GLNF sorting, with the purpose of enhancing the discrimination of alternatives located on the border between categories. In addition, the proposed method has been validated with a real customer segmentation case involving thousands of alternatives, complemented by a sensitivity analysis to demonstrate the robustness of the classification results.

3. Methodology: PROMETHEE

This section explains how to calculate the PROMETHEE net flows which are necessary to apply the algorithm proposed in this research. To apply PROMETHEE, the process begins with an evaluation table, as presented in Table 2. In this table, the set of alternatives $A = \{a_1, a_2, \ldots, a_i \ldots, a_n\}$, the set of criteria in the dimension to be evaluated $G = \left\{g_1, g_2 \ldots, g_j, \ldots, g_m\right\}$, and their respective weights $W = \{w_1, w_2 \ldots, w_j, \ldots, w_m\}$ are specified.

Table 2. Evaluation table.

Alternatives	Evaluation Criteria					
	g_1	g_2	$\cdots$	g_j	$\cdots$	g_m
	w_1	w_2		w_j		w_m
a_1	$g_1(a_1)$	$g_2(a_1)$	$\cdots$	$g_j(a_1)$	$\cdots$	$g_m(a_1)$
a_2	$g_1(a_2)$	$g_2(a_2)$	$\cdots$	$g_j(a_2)$	$\cdots$	$g_m(a_2)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
a_i	$g_1(a_i)$	$g_2(a_i)$	$\cdots$	$g_j(a_i)$	$\cdots$	$g_m(a_i)$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\ddots$	$\vdots$
a_n	$g_1(a_n)$	$g_2(a_n)$	$\cdots$	$g_j(a_n)$	$\cdots$	$g_m(a_n)$

Initially, this method calculates the bidirectional preferences between each pair of alternatives. For example, it assesses how much alternative a_i is preferred over alternative a_q for all criteria and vice versa. To determine this preference, the deviation d_j between alternatives a_i and a_q for criterion j is initially computed. This deviation, denoted as $d_j(a_i, a_q)$, is then transformed into a preference scale P_j from 0 to 1, using a defined preference function F_j. Thus, $P_j(a_i, a_q) = F_j\left[d_j(a_i, a_q)\right]$, where $0 \leq P_j(a_i, a_q) \leq 1$.

There are six principal types of preference functions: usual, u-shape, level, v-shape, linear, and Gaussian. Each of these functions models DMs' preferences based on the calculated deviation values for d_j. These functions have a preference threshold p, indicating from which deviation value d_j there is an absolute preference for a_i. Additionally, the functions have an indifference threshold q, indicating from which deviation value d_j the preference for a_i begins to increase. The usual and v-shape functions have an indifference threshold of zero. The way preference increases in each function varies. For example, in usual function, any deviation $d_j(a_i, a_q) > 0$ results in an absolute preference $P_j(a_i, a_q) = 1$, while in the linear function, when $d_j(a_i, a_q) \leq q$, then $P_j(a_i, a_q) = 0$, if $d_j(a_i, a_q) \geq p$, then $P_j(a_i, a_q) = 1$, or if $q \leq d_j(a_i, a_q) \leq p$, then $P_j(a_i, a_q)$ increases linearly with a slope equal to $1/(p-q)$.

Once the preferences of a_i over a_q have been calculated for each of the criteria, the Aggregated Preference Index (API) is then computed following this Equation:

$$\pi(a_i, a_q) = \sum_{j=1}^{m} P_j(a_i, a_q) \cdot w_j. \tag{1}$$

The API must be calculated for all alternatives $\pi(a_i, x)$, so that subsequently, through averaging, the positive outranking flow is computed as shown below:

$$\varphi^{+}(a_i) = \frac{1}{n-1} \sum_{x \in A} \pi(a_i, x). \tag{2}$$

As preference is bidirectional, the API reflecting how much each of the other alternatives is preferred to a_i, denoted as $\pi(x, a_i)$, must be calculated. These results are averaged to compute the negative outranking flow as follows:

$$\varphi^{-}(a_i) = \frac{1}{n-1} \sum_{x \in A} \pi(x, a_i). \tag{3}$$

The outranking flows obtained in Equations (2) and (3) lead to a partial ranking of alternatives known as PROMETHEE I. To proceed to PROMETHEE II, the net flow for each alternative must be calculated. This net flow results from subtracting the negative outranking flow from the positive outranking flow, expressed as follows:

$$\varphi(a_i) = \varphi^{+}(a_i) - \varphi^{-}(a_i). \tag{4}$$

The methodology proposed in this study relies on the signs and values of the net flows in PROMETHEE II. For a more in-depth understanding of the steps and preference functions involved in the PROMETHEE method, refer to Brans and De Smet [38].

4. Multicriteria Classification Method

4.1. The GLNF Matrix Classification Algorithm

This classification algorithm is characterised by having a complete classification of alternatives, where each alternative can be assigned to a single group from a matrix formed by two relevant dimensions, integrating several evaluation criteria. The method shares the concepts and strategy of global and local searches proposed in the GLNF sorting algorithm [8,16]. Local searches enhance the accuracy of the pre-classifications obtained through the global search.

The algorithm divides the alternatives according to the positive and negative signs of the PROMETHEE net flows, in accordance with the property demonstrated by Rosenfeld and De Smet [39], as the alternatives with positive net flows are strongly preferred over the rest.

The aim is to classify alternatives into four segments, using two dimensions: D_1 and D_2, which represent the horizontal and vertical axis, respectively. Where, $S(D_1) = \{s_1, s_2 \ldots, s_j, \ldots, s_m\}$ for the criteria set of dimension 1, and $H(D_2) = \{h_1, h_2 \ldots, h_j, \ldots, h_n\}$ for the criteria set of dimension 2. The evaluation criteria have associated weights and their sum is equal to one for each dimension.

To define the four segments, six limiting profiles are established, distributed in three profiles for each dimension, i.e., the sets $R(D_1) = \{r_1, r_2, r_3\}$ and $R(D_2) = \{r_4, r_5, r_6\}$. These limiting profiles have the following values of net flow: the best is 1, the worst is -1, and the zero net flow is in the middle to divide both sets of alternatives, those with positive net flow from those with negative net flow. The limiting profiles allow for distinguishing between preferred (with net flow between 0 and 1) and non-preferred (with negative net flow) alternatives. Thus, considering that this method is designed to categorise into four groups, the values of the limiting profiles are as follows: $R(D_1) = \{-1, 0, 1\}$ and $R(D_2) = \{-1, 0, 1\}$. It should be mentioned that these values could vary depending on the scale used to calculate the net flow. The three limiting profiles of both dimensions are combined to form a four-quadrant matrix, as illustrated in Figure 1. The steps to apply the algorithm are as follows:

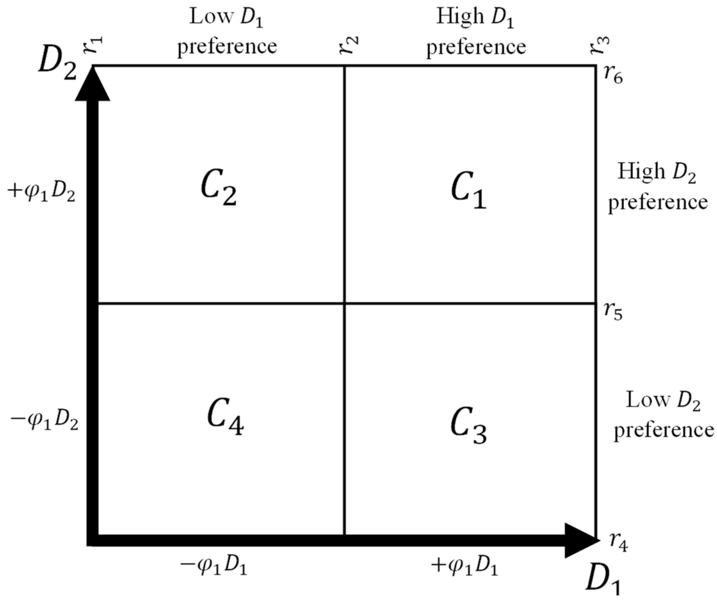

Figure 1. Matrix of segments from global search by D_1 and D_2 dimensions.

Step 1: Data. Before starting the classification procedure, thorough data preparation is essential. This includes the collection and organisation of the alternatives (customers) in the set A, as well as the definition of the PROMETHEE input parameters of the set of evaluation criteria that make up the dimensions D_1 and D_2: $S(D_1)$ and $H(D_2)$. Consequently, two evaluation tables will be generated, one for each dimension.

Step 2: Global search. PROMETHEE is applied to dataset A, to evaluate the alternatives according to their criteria in each dimension. The net flows obtained (φ_1) are $(\varphi_1 D_1)$ for D_1 and $(\varphi_1 D_2)$ for D_2. Each dimension is divided into two sets according to the sign of φ_1 (high preference $+\varphi_1$ and low preference $-\varphi_1$).

In Figure 1, the pre-classified alternatives in C_1 with $+\varphi_1$ (high preference) for D_1 and D_2 are in quadrant I. In quadrant II, C_2 includes alternatives with high preference in D_2 and low preference in D_1. In quadrant IV, C_3 includes the alternatives with high preference in D_1 and low preference in D_2. Alternatives with low preference $(-\varphi_1)$ in D_1 and D_2 are pre-classified in group C_4, which is located in quadrant III. It is important to note that the alternative assignment in Figure 1 is determined by its net flow value on both axes, but its position in the quadrant, and hence its pre-classifying, depends solely on the sign associated with the net flow and its comparison with the limiting profiles.

Step 3: Intra-segments local search by dimension. As the dimensions have been divided using the limiting profiles to classify alternatives according to the φ_1 sign (called $D_n^{+\varphi_1}$ or $D_n^{-\varphi_1}$, where n is the dimension number), PROMETHEE is then applied to the alternatives of the segments defined in the global search to calculate the net flows (φ_2). This involves applying PROMETHEE four times: one for the alternatives defined between

r_1 and r_2 in D_1, one for those defined between r_2 and r_3 in D_1, one for those defined between r_4 and r_5 in D_2, and finally, another for alternatives defined between r_5 and r_6 in D_2.

Then, according to the sign of φ_2, the alternatives are subdivided into two groups in each subdimension: those preferred with positive or zero φ_2 and those not preferred with negative φ_2. Figure 2 depicts the first local searches by subdimension. Figure 2a illustrates the application of the local searches for D_1, where PROMETHEE is applied to the pre-classified alternatives in C_1 and C_3 belonging to the subdimension $+\varphi_1 D_1$, called $\varphi_2 D_1^{+\varphi_1}(C_1C_3)$. Similarly, φ_2 is calculated for the alternatives with $-\varphi_1 D_1$ pre-classified in groups C_2 and C_4 ($\varphi_2 D_1^{-\varphi_1}(C_2C_4)$). Figure 2b represents areas where φ_2 is calculated for the subdivisions of D_2, calculating $\varphi_2 D_2^{+\varphi_1}(C_1C_2)$ and $\varphi_2 D_2^{-\varphi_1}(C_3C_4)$. Figure 2c,d show the resulting partitions after the second local search, where a further internal subdivision occurs in each subdimension according to the sign of φ_2.

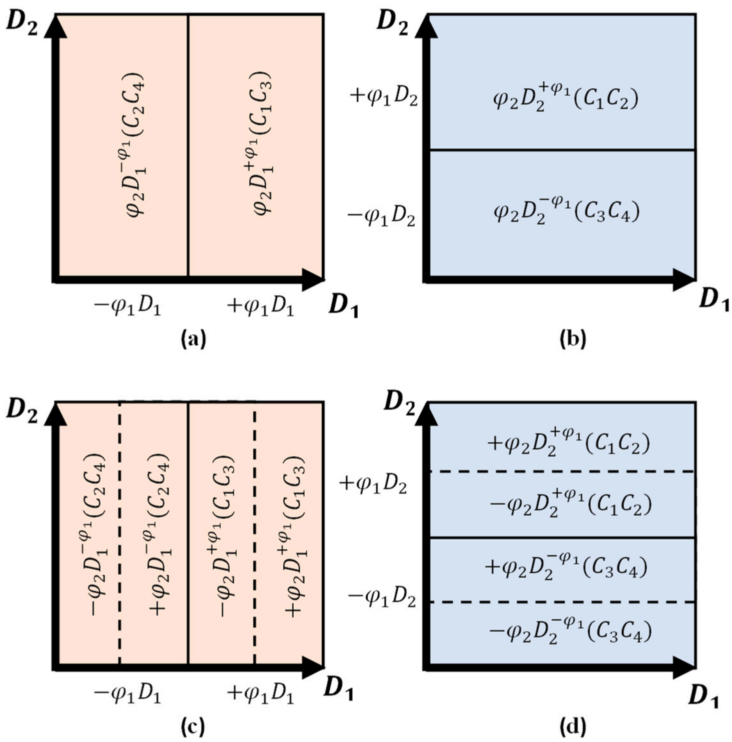

Figure 2. Intra-segments local search for dimensions D_1 and D_2: (**a**) local search for D_1; (**b**) local search for D_2; (**c**) local search results for D_1; (**d**) local search results for D_2.

Step 4: Second local search. Using the information obtained in the previous step, the net flows (φ_3) are calculated by applying PROMETHEE to the non-preferred alternatives of the upper subdimension with the preferred alternatives of the lower subdimension. Figure 3 shows in red the areas where φ_3 is calculated for D_1 and in blue for D_2. The purple region represents the area with the alternatives for which φ_3 is calculated in both D_1 and D_2, with the alternatives in this border area requiring a higher level of detail in the search. The alternatives in the grey areas, located at the vertices, are those which, after the first local search, did not fall into any border region between groups. Therefore, they are not subjected to a second local search and go directly from step 3 to step 5 of the algorithm.

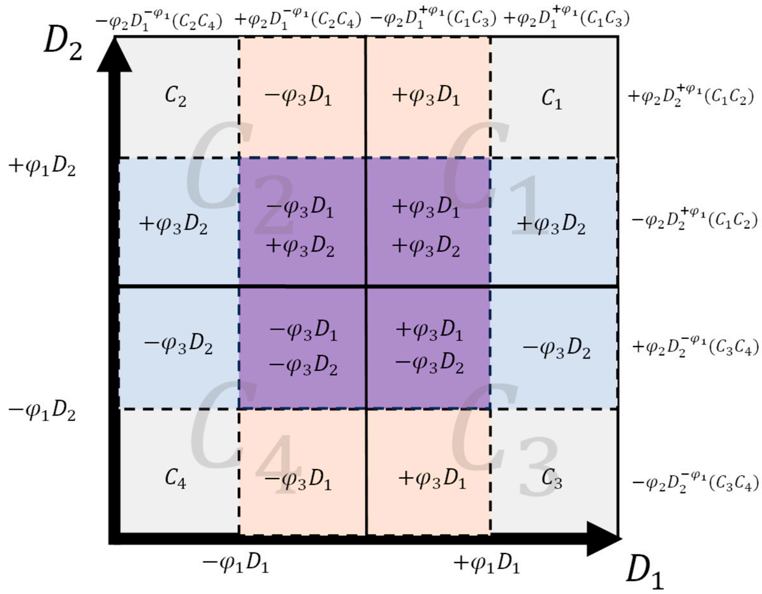

Figure 3. Final matrix classification of alternatives based on dimensions D_1 and D_2.

For example, Figure 3 shows, in the upper-right corner (grey area), that the alternatives that obtained $+\varphi_2 D_1^{+\varphi_1}(C_1C_3)$ and $+\varphi_2 D_2^{+\varphi_1}(C_1C_2)$-positive net flow are definitely classified in C_1 (not calculated φ_3), while the alternatives pre-classified in C_1 that obtained $-\varphi_2 D_1^{+\varphi_1}(C_1C_3)$ and $-\varphi_2 D_2^{+\varphi_1}(C_1C_2)$ negative net flow must undergo a second local search to calculate φ_3 for both D_1 and D_2. This interpretation applies in the same way for the other areas.

Step 5: Final classification: The final classification is determined by the φ_3 sign calculated in the second local search. For results of positive or equal-to-zero φ_3, the alternative will be assigned to the adjacent group with the highest preference in the evaluated dimension. On the contrary, alternatives with φ_3-negative values will be assigned to the lowest preference adjacent group in the dimension evaluated.

For example, as Figure 3 shows, after calculating φ_3 among the alternatives with $+\varphi_2 D_1^{-\varphi_1}(C_2C_4)$ and $-\varphi_2 D_1^{+\varphi_1}(C_1C_3)$, those with positive or equal-to-zero φ_3 should definitely be assigned to the group on the right, which has a higher preference in D_1. This means that the pre-classified alternatives in C_2 and C_4 that satisfy this condition should be reallocated to C_1 and C_3, respectively.

The alternatives in the violet area may be reallocated or not in one or both dimensions. For example, after calculating φ_3 among the alternatives with $+\varphi_2 D_1^{-\varphi_1}(C_2C_4)$ and $-\varphi_2 D_1^{+\varphi_1}(C_1C_3)$, and also from calculating φ_3 among the alternatives with $+\varphi_2 D_2^{-\varphi_1}(C_3C_4)$ and $-\varphi_2 D_2^{+\varphi_1}(C_1C_2)$, the alternatives with $+\varphi_3 D_1$ and $+\varphi_3 D_2$ are definitely assigned to C_1. In contrast, those that obtained negative values $-\varphi_3 D_1$ and $-\varphi_3 D_2$ are assigned to C_4, while alternatives with negative net flow $-\varphi_3 D_1$ and positive net flow $+\varphi_3 D_2$ are assigned to C_2, and those $+\varphi_3 D_1$ and $-\varphi_3 D_2$ are assigned to C_3. The algorithm pseudocode is shown in Appendix A.

4.2. Empirical Case: Consumer Segmentation in a Packaged Consumer Goods Sector

The proposed segmentation algorithm has been validated by real data used in Barrera et al.'s study [8]. This database contains records of 8157 customers of a multinational with manufacturing in the country (Colombia). This company specialises in the production of healthcare products and distributes through other companies in a B2B model.

Figure 4 shows the hierarchy of criteria with two relevant dimensions, which integrate three evaluation criteria each, to carry out the customer classification. The first dimension corresponds to RFM, with an economic focus, allowing for the assessment of the customer's transactional performance by considering the time elapsed since the last purchase (recency), the frequency of purchase in the period evaluated (frequency), and the amount of purchase in that period (monetary).

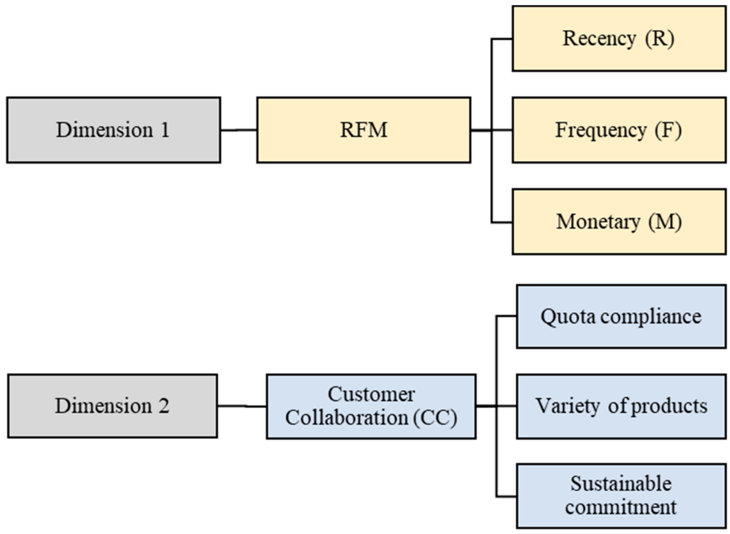

Figure 4. Criteria for dimensions D_1 and D_2.

The second dimension, CC, focuses on measuring the degree of sustainable customer collaboration. This collaboration is assessed through criteria such as compliance with the purchase quota negotiated with customers (quota compliance). The quota compliance is calculated using Equation (5), where $QC(a_i)$ represents the percentage of the customer's compliance, M_T is the total amount purchased, and M_{qT} is the minimum purchase quota.

$$QC(a_i) = \left(\frac{M_T}{M_{qT}}\right) \cdot 100\%. \tag{5}$$

The rating is according to the variety of products purchased, where the proportion of purchases per product and sustainable commitment are measured (variety of products). The variety of products is calculated using Equation (6), where $VP(a_i)$ represents the customer's score. This score compares the actual proportion of the customer's purchase of each product P_j to the ideal share defined by the company.

$$VP(a_i) = \sum_{j=1}^{n} \min\left(\frac{M_{TP_j}}{M_T}, W_{P_j}\right) \cdot 100. \tag{6}$$

where M_{TP_j} is the amount purchased of product P_j, and W_{P_j} is the ideal proportional share. With the exception of recency, all other criteria are aimed at maximisation.

The inclusion of two dimensions, RFM and CC, is interesting to carry out a segmentation of customers into quadrants. These criteria provide an integrated view of buying behaviour and level of collaboration, allowing for a more precise and strategic classification based on sustainable relationships.

Table 3 details the weights assigned to each of the criteria for both dimensions assessed (these weights are calculated as a proportion based on the weights defined in Barrera et al. [8] so that both dimensions weigh the same). The overall assessment of the weight variation is between the specific criteria. The most significant criterion for the first dimension, RFM, is monetary, which represents 65.07%, while for the second dimension it corresponds to variety of products with a weight of 66.06%.

Table 3. Criteria weights for two dimensions.

Dimension	Criterion	% Weight
RFM	Recency	12.15
	Frequency	22.78
	Monetary	65.07
Customer collaboration	Quota compliance	20.61
	Variety of products	66.06
	Sustainable commitment	13.33

5. Results

This Section presents the results of the steps of the proposed method for the empirical case of customer segmentation. To automate the algorithm's calculations, a new R programming language code has been developed and is provided in the Supplementary Materials. The code calculates the net flows by importing the function 'PROMETHEEII', which is part of the R software package 'PrometheeTools' [40]. Data are imported from a Microsoft Excel file using 'read_excel' function [41]. All executions were carried out using RStudio Team [42].

5.1. Global Search

The scatter plot of the net flows of the alternatives obtained from the global search after applying PROMETHEE to each of the RFM and CC dimensions is shown in Figure 5. In this analysis, a total of 8157 customers were pre-classified into one of four segments. In the C_1 group, 2673 customers were pre-classified, characterised by positive net flow values for both CC dimension ($+\varphi_1$CC) and RFM dimension ($+\varphi_1$RFM). In group C_2, 1439 customers with positive CC net flow ($+\varphi_1$CC) and negative in RFM ($-\varphi_1$RFM) were pre-classified. Group C_3, characterised by positive RFM and negative CC net flows, includes 771 customers. Lastly, group C_4 includes 3274 customers with negative values in the net flows of both dimensions.

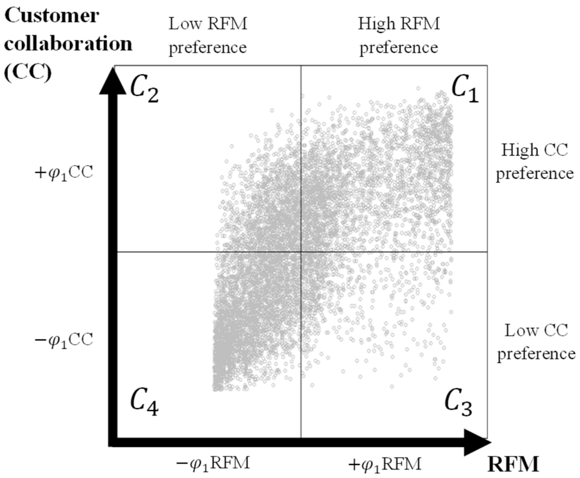

Figure 5. Global search results: scatter plot of alternatives net flow.

5.2. Intra-Segments Local Search by Dimension

Figure 6a shows the results obtained by the intra-segments local search. In particular, customers with positive net flow ($+\varphi_2$) are shown in red, and in black, those with negative net flow ($-\varphi_2$) are shown, obtained by applying PROMETHEE in the RFM dimension with flows $+\varphi_1$ and $-\varphi_1$, which were previously generated by the global search step (see Figure 5).

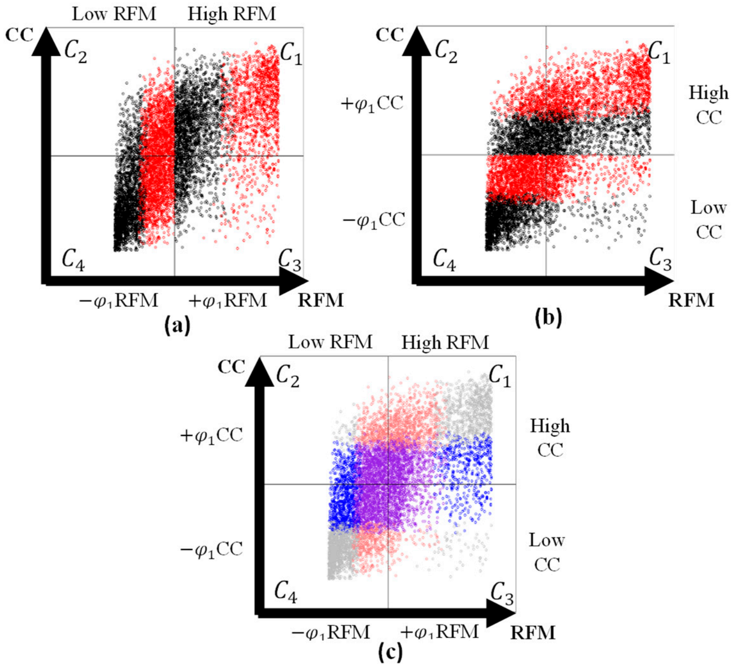

Figure 6. Intra-segments local search for RFM and CC dimensions: (**a**) local search for RFM; (**b**) local search for CC; (**c**) local search results for the RFM and CC.

For example, for the subdimension with $+\varphi_1$ of RFM, it can be observed that after applying the intra-segments local search, in the right part marked in red (with result $+\varphi_2\mathrm{RFM}^{+\varphi_1}(C_1C_3)$), 1303 customers with a higher preference in this dimension are found. Therefore, they will not be included in the second local search for D_1. However, the 2141 customers marked in black ($-\varphi_2\mathrm{RFM}^{+\varphi_1}(C_1C_3)$) are the least preferred in the subdimension $+\varphi_1$RFM and are therefore included in the second local search along with the 2443 most preferred customers of the subdimension $-\varphi_1$RFM ($+\varphi_2\mathrm{RFM}^{-\varphi_1}(C_2C_4)$).

There are 4584 customers to which a second local search in RFM would be applied, as they lie on the border separating groups C_1 and C_3 from groups C_2 and C_4. Finally, the 2270 customers marked in black in the subdimension $-\varphi_1$RFM ($+\varphi_2\mathrm{RFM}^{-\varphi_1}(C_2C_4)$) are the lowest preferred in RFM, so they cannot improve on this axis and will not be included in a second local search for this dimension.

Figure 6b presents the results of the first local search for the CC dimension. As with the RFM dimension, preferred and non-preferred customers can be visually identified within each intra-segments search but this time for the CC dimension. A second local search is required for 4376 customers located on the border between groups C_1 and C_2, characterised by high preference values in CC, and groups C_3 and C_4, with low preference. In detail, this second local search in CC is necessary for 2192 customers with $-\varphi_2\mathrm{CC}^{+\varphi_1}(C_1C_2)$ and 2184 customers with $+\varphi_2\mathrm{CC}^{-\varphi_1}(C_3C_4)$.

In this step, 1920 pre-classified customers in C_1 and C_2 who obtained positive values $+\varphi_2$, as well as the 1861 pre-classified customers in C_3 and C_4 with negative values $-\varphi_2$, do not need to be considered in a second local search for CC dimension. The former are the most preferred in their segment and the latter are the least preferred.

Figure 6c represents the results of the local search 'intra-segments' by both dimensions. In grey are marked 2244 customers who do not require a second local search in any of the dimensions evaluated. Their final classification corresponds to that of the global search. In light coral, 1537 customers are marked as requiring a second local search only by the RFM dimension. In blue are 1329 customers that will be subject to a second local search exclusively by the CC dimension. Finally, in purple, 3047 customers are identified close to the border shared by the four groups. These customers are included in the second local search for both dimensions evaluated.

5.3. Second Local Search

The results of the second local search are plotted in Figure 7, where 153 customers marked in red were reallocated to a group with a higher preference in RFM. In blue, 161 customers are identified as having been reallocated to a group with a higher preference in CC. In black, 112 customers have been reallocated to a group with a lower preference in RFM and/or CC. The four customers marked in purple have moved from being in a group with better preferences in both RFM and CC. In yellow, two customers are highlighted who have been reassigned to a group with a higher preference in RFM but a lower preference in CC. In grey, 7729 customers are shown as remaining in the same group that was assigned to them in the global search. This brings the total number of reassigned customers to 428.

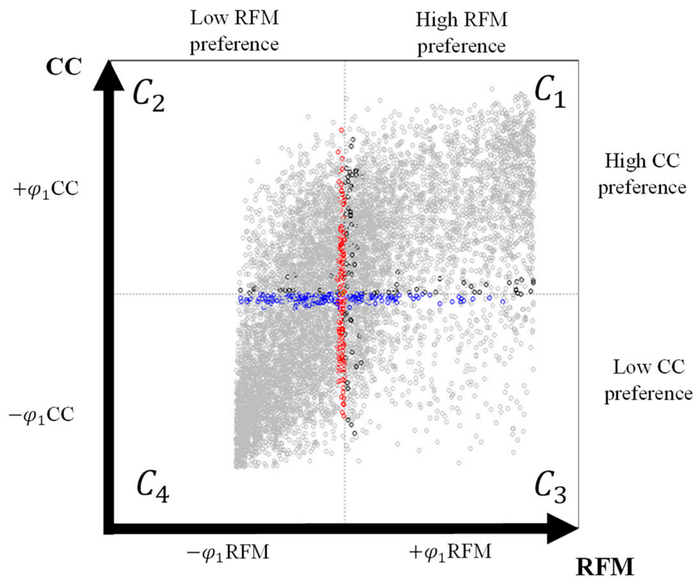

Figure 7. Results from second local search.

5.4. Final Classification of the Alternatives

Figure 8 shows the scatter plot of the final classification of 8157 customers into four groups generated by RFM and CC dimensions. The colour labels represent the final classification, and the plotted net flow values for each customer correspond to the global search. Marked in blue are 2746 customers classified in group C_1, with high preference in RFM and CC. In red, there are 1478 customers classified in group C_2, sharing characteristics of high preference in CC and low preference in RFM. In total, 796 customers marked in purple were classified in C_3, characterised by high preference in RFM and low preference in CC. Finally, 3137 customers classified in C_4 were labelled in green; these customers share characteristics of a low preference for both dimensions. Considering that both axes have the same weight in the evaluation, it can be concluded that group C_1 is preferred over group C_4. However, preference between other groups cannot be established based on the results obtained in the RFM and CC dimensions.

Table 4 presents the average values of the criteria assessed for the four customer groups. The C_1 group has the highest average values for most criteria, indicating high performance in both dimensions. In contrast, group C_4 has the lowest average values for most of them. Group C_2 stands out for having high average values in "Variety of products" and "Sustainable commitment", which makes it stand out in the CC dimension. However, it has low values for "monetary" and "frequency", indicating a low preference in the RFM dimension. Group C_3 exhibits remarkable average values in all RFM criteria, while its average values in the CC dimension are worse.

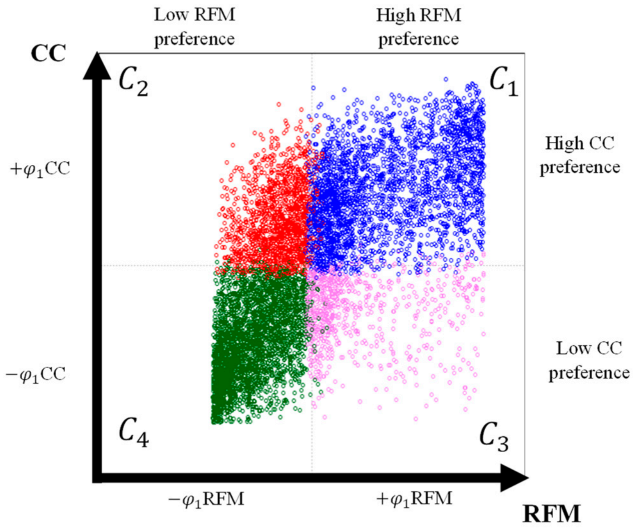

Figure 8. Final classification of the alternatives.

Table 4. Average values by criteria according to the final customer classification.

Group	Recency	Frequency	Monetary	Quota Compliance	Variety of Products	Sustainable Commitment
C_1	0.14	10.78	180.15	36.6	76.32	3.04
C_2	1.42	6.24	35.01	6.7	73.08	3.20
C_3	0.19	10.31	137.63	9.7	58.39	2.75
C_4	2.87	3.96	15.59	1.1	48.51	2.90

Finally, the segments generated by the proposed classification algorithm can be characterised as follows:

Group C_1: (strategic customers): The performance of these customers presents high preference in both dimensions. Customers in this group make frequent purchases of significant value, and their transactions are relatively recent. These customers consistently meet or exceed purchase quotas, buy a wide variety of products, and demonstrate a strong commitment to sustainability. This group, consisting of preferred and sustainable partners, is distinguished by its strategic importance to the company. Through exclusive loyalty programmes, these customers could further strengthen their role as long-term partners. Their opinions represent valuable feedback to be taken into account in developing innovations and improvements. Additionally, their active participation in collaborative initiatives and high level of transactionality make them an integral part of the company's sustainable growth strategy, enabling the establishment of mutually beneficial relationships.

Group C_2 (collaborative customers): This group includes customers with a high level of collaboration but low transactional performance (RFM). These customers collaborate effectively by meeting quotas and purchasing a diverse range of products, with attention to sustainability. However, customers in this group tend to purchase less frequently, make smaller purchases, and their transactions are less recent. To understand the factors that may be influencing their less frequent and lower-value purchases, a detailed analysis is required. This analysis should address other variables, such as the customer's sales maturity, possible limitations or common demographic patterns, and the level of knowledge about the products being marketed. Through this specialised analysis, it can be determined whether the transactional RFM behaviour of these customers has potential to improve over time, whether they are influenced or constrained by specific consumer demographic segments, or whether lack of product knowledge plays a role. Overall, the collaborative disposition of these customers can be used as a starting point for further analysis and, if possible, to improve their sales.

Group C_3 (transactional customers): These customers stand out for making significant purchases with high frequency but show a low level of collaboration. Customers in this segment make frequent and high-value purchases within recent periods. However, they may not fully meet quotas or purchase a wide variety of products. Additionally, their commitment to sustainable practices is lower. They represent a valuable opportunity to strengthen the relationship. It is critical to expose them to the tangible benefits that would arise from increased levels of collaboration between the parties. While these customers might be considered less loyal compared to other groups, it is important to consider future alternatives to counteract possible defections. The characterisation of these customers suggests that they may value their participation in inventory clearance campaigns more than in campaigns designed to build sustainable long-term relationships.

Group C_4 (non-preferred customers): Customers in this group show low scores in both RFM transactions and collaboration. Purchases are infrequent and of low value, and their level of collaboration is weak. These customers tend not to meet purchase quotas, buy few product varieties, and show limited interest in sustainability. It is essential to carry out a detailed profitability assessment for this set of customers. If the cost of maintaining the relationship with these customers exceeds the value they bring, it may not be sustainable in the long term. Through careful prioritisation, identifying those customers that are closer to the border with the other groups, selective reactivation or retention campaigns could be implemented, allowing some customers to improve their profitability and hence their classification. However, it is important to monitor the cost associated with implementing strategies for these types of customers. If, despite efforts, some customers continue to show low scores, they may not ultimately be profitable.

5.5. Classification Compared to an Alternative Method

The definitive classification has been compared with the one obtained only with the PROMETHEE global search, which has been used in the literature by Casas-Rosal et al. [19] to classify consumers and Segura and Maroto [14] for suppliers. This method groups alternatives in four quadrants according to the sign of their net flow but without refining assignments with local searches.

Table 5 shows the contingency matrix where 7729 customers are classified in the same groups by both methods, while 428 customers are classified in different groups. For both cases, group C_4 has the highest number of customers classified, followed by group C_1, C_2, and finally, C_3.

Table 5. Contingency matrix between proposed and alternative method.

		Alternative Method				
		C_1	**C_2**	**C_3**	**C_4**	
Proposed method	C_1	2599	78	65	4	2746
	C_2	42	1340		96	1478
	C_3	32	2	689	73	796
	C_4		19	17	3101	3137
		2673	1439	771	3274	8157

5.6. Sensitivity Analysis

An extensive sensitivity analysis was carried out to test the robustness of the proposed method. Changes were made to the parameters related to the criteria weights, as well as to the indifference and preference thresholds of preference functions. The criteria weights were modified simultaneously, with random increases and decreases in the percentages of the initial values, ranging from −10% to 10%, −20% to 20%, −30% to 30%, and −40% to 40%.

Sensitivity to changes in the parameters of the preference functions was gauged by randomly selecting them from a set of predefined indifference and preference threshold (see Appendix B, Table A1). For each of the sensitivity tests, 100 iterations were generated covering different random variations as mentioned above. Subsequently, the average number of customers who had changed their initial classification after applying the variation in each iteration was calculated. Table 6 presents the average results of the 100 iterations for each scenario, showing the average number of changes in customer classification ($\bar{\Delta}$Cu) and the percentage this represents of the total number of customers ($\bar{\Delta}$%). The results are presented for both the proposed and the alternative method.

Table 6. Sensitivity analysis: average number of customers reclassified.

Method	**Criteria Weights Variations**								**Thresholds Variation**	
	[−10%, 10%]		**[−20%, 20%]**		**[−30%, 30%]**		**[−40%, 40%]**			
	$\bar{\Delta}$Cu	**$\bar{\Delta}$%**	**$\bar{\Delta}$Cu**	**$\bar{\Delta}$%**	**$\bar{\Delta}$Cu**	**$\bar{\Delta}$%**	**$\bar{\Delta}$Cu**	**$\bar{\Delta}$%**	**$\bar{\Delta}$Cu**	**$\bar{\Delta}$%**
Proposed	46.41	0.57	116.06	1.42	175.83	2.16	251.06	3.08	365.22	4.48
Alternative	419.01	5.14	441.4	5.41	462.34	5.67	463.97	5.69	508.85	6.24

Table 6 shows how the results change between the proposed and the alternative method by varying the criteria weights and preference function thresholds. For example, the first column indicates that, on average, 46.41 customers changed their initial classification by randomly modifying the criteria weights in the range of [−10%, 10%]. This represents a reallocation of 0.57% of the total number of customers. This result contrasts with the 419.01 average customers who changed their classification with the alternative method when subjected to the same variations. As the ranges of variation widen, the number of changes in their classifications increases in the proposed method. However, the alternative method barely registers increases; although, its average values are always considerably higher than those obtained with the proposed method. As for the variations in the thresholds of the preference functions, the results in Table 6 indicate that, on average, the proposed method undergoes fewer changes in the initial classification (365.22), compared to the alternative method (508.85). Finally, in all scenarios, it is observed that the proposed method is less sensitive to parameter variation than the alternative based only on a global search.

6. Discussion

This research provides a new multicriteria approach, called GLNF matrix classification, for the complete classification of alternatives into four segments based on two dimensions, where each dimension represents a set of criteria. The algorithm classifies alternatives based on PROMETHEE net flows in global and local searches. The assignment of alternatives to groups depends on the positive or negative sign of their net flow. These net flows are calculated based on the company's preferences regarding its customers. This method has been programmed in R language and validated using the RFM and CC dimensions, to segment 8157 customers into four groups: strategic, collaborative, transactional, and non-preferred customers. This type of segmentation makes it possible to formulate specific strategies for each group with a significant impact on improving the company's sustainable CRM practices. The proposed method is not only a valuable decision support tool but can also be incorporated into a DSS and artificial intelligence tools, enhancing the company's ability to implement more accurate and focused actions to strengthen its relationship with customers.

The application of global and local searches to segment alternatives based on the sign of the net flow is an essential concept of the GLNF sorting algorithm, which has previously been used by Barrera et al. [16] and Barrera et al. [8] in the ordered classification of suppliers and customers, well known as the sorting problem. In contrast, GLNF matrix classification is specifically designed for cases where groups are differentiated in specific multicriteria dimensions, assigning alternatives to four non-ordered groups. This approach enables nuanced segmentation, allowing companies to group customers based on high or low preferences in critical independent dimensions, thereby offering more flexible information for personalised strategies. There is also a distinction in the definition of the limiting profiles used in the global search. GLNF classification requires less cognitive effort from the decision-maker, as it does not require defining limiting profiles to separate categories; instead, this separation is achieved automatically based on the net flow sign property demonstrated by Rosenfeld and De Smet [39]. Therefore, although sharing the same concept of GLNF sorting local searches, there is a fundamental difference in the definition of objectives between the two algorithms and, as a result, in their applications in DSS and artificial intelligence tools. The proposed algorithm is useful when seeking to identify and characterise segments according to two criteria dimensions without establishing a hierarchy of preference among them.

Comparing the multicriteria methods published in the literature with the proposed classification algorithm, it can be stated that they all use limiting profiles to establish the segmentation structure in the global search. However, in the proposed local searches, close alternatives are compared, taking into account the sign of their net flows. This comparison between alternatives that are close in preferences allows for improved classification, especially when a large number of alternatives are involved. Another difference is that some methods in the literature may require DMs to set values per criterion to construct a set of limiting profiles, prototypes, or thresholds that define the categories (e.g., [24,32,33]). The method proposed in this research does not require this effort. As mentioned above, the limiting profiles are predefined by the property of the sign of the net flow, discriminating between preferred and non-preferred alternatives [39].

In customer segmentation, it is important to present information clearly, so that communications are accurate and facilitate the development of strategies and tactics [22]. The proposed method facilitates the identification and characterisation of what each group represents in terms of the dimensions considered, as illustrated in Figure 8. Likewise, it is possible to analyse not only the final results, but also the results of each of the steps of the algorithm, as shown in Figures 5–7. Additionally, compared to other MCDM methods based on two dimensions matrix classification [14,15,19,27], the proposed method, using local searches, addresses the problem of uncertainty that may arise when classifying alternatives on the border of two or more categories. In other words, this method provides valuable information that is obtained through a rigorous procedure of comparing alternatives, based on multiple criteria that reflect the preferences and objectives of the company. The results provide information that is straightforward to interpret, making it easier for the company's managers to use it effectively to make decisions.

The PROMETHEE method requires the weights of the criteria and an effort of the DMs to establish the preference functions [2]. This need can be considered a disadvantage of algorithms based on this method, as setting the preference functions and their parameters in line with the needs of the company can be complicated. For this reason, the robustness of these algorithms plays a crucial role in DSS and artificial intelligence tools. The sensitivity analysis presented in Table 6, which includes a comparison with the alternative method based on PROMETHEE from the literature [14,15,19], shows that, thanks to the reallocations of local searches, the proposed algorithm is remarkably less sensitive to changes in parameter values typical of real contexts. This robustness is essential in real-world scenarios, where the channelling of decision-makers' preferences when defining parameters may involve a degree of uncertainty. Finally, in both methods, the interpretation of alternatives is carried out in a 2×2 matrix, formed by two critical dimensions.

This method contributes significantly to research related to multicriteria classification, and, in particular, to customer segmentation. This research fulfils a real segmentation need that has been addressed so far mainly by other techniques, such as clustering. Moreover, no method based exclusively on multicriteria techniques has been found that segments a large number of customers into groups, as presented in this paper (8157 customers). Previous studies have mainly focused on smaller scale applications of alternatives, being almost always less than 30 (e.g., [27,31]).

The proposed algorithm has great advantages in the interpretation of the results. However, the evaluation criteria, which will integrate the two main dimensions, need to be well defined. Therefore, it is crucial that the criteria integrating two dimensions are aligned and provide relevant information. To achieve this alignment, methods such as Analytic Hierarchy Process can be employed to establish the hierarchies and weights of the criteria within each dimension. There is also a disadvantage in setting a fixed number of groups (four); although, this is an adequate number to establish marketing strategies and is aligned with the average number of groups used in other methods (see Table 1). Moreover, as it does not require subsequent intervention by DMs, it facilitates decision-making, especially in conditions with a large number of alternatives. This method follows a Type 1 complete-classification approach, assigning each alternative to only one group. Therefore, it is not suitable for contexts where alternatives may be assigned to multiple groups and/or remain unclassified.

Finally, the adoption of the MCDM approach to matrix classification, as presented in this research, has the potential to extend to other areas of sustainable supply chain management, other sectors, as well as problems related to human resources management, and education, among others. In purchasing portfolio models, this approach could be used to enhance the consideration of multiple criteria, as well as the lines of demarcation between groups and the measurement of criteria, which are issues that have already been discussed ([23]). The proposed method can be specifically applied, for example, in contexts to classify products, suppliers, or projects based on their environmental impact, profitability, risk, opportunity, strategic value, etc. Overall, it could be used to facilitate decision-making based on multiple criteria that require classifying elements into two critical dimensions, thus forming a classification matrix.

7. Conclusions

This research provides a novel method designed to classify supply chain alternatives based solely on multicriteria techniques. The groups are represented in the quadrants of a matrix according to evaluation criteria that are integrated in two dimensions. The classification algorithm is based on the properties of PROMETHEE II net flows, together with the concepts of global and local searches. Initially, a pre-classification is carried out by means of a global search, where the limiting profiles define the quadrants of the matrix. Then, this classification is refined through two local searches, which consider comparisons of alternatives with close preferences in each dimension. After these local searches, some alternatives are reassigned to a more appropriate group, while others retain their original classification.

This method has been validated using real data to segment 8157 customers of a multinational company that manufactures and distributes healthcare products. The dimensions of RFM and CC were used, comprising criteria that promote both economic and customer collaboration. The results enabled their classification into four groups: strategic, collaborative, transactional, and non-preferred. Strategic customers are sustainable and exhibit high levels of preference in both dimensions, while collaborative customers show a high preference in the CC dimension but a low preference in RFM. Transactional customers show high preference in the RFM dimension but low preference in terms of their level of collaboration. Finally, non-preferred customers show low preferences in both dimensions. The identification of these groups allowed for a detailed characterisation of the customers in order to improve CRM.

The consistency of the classification results obtained with the method has been confirmed through a sensitivity analysis by changing critical parameters, such as criteria weights and thresholds in preference functions. It is crucial to recognise that these parameters may be some degree of uncertainty due to the cognitive effort required to determine them. However, the results of this evaluation indicate that, in the face of different parameter modifications, the proposed method maintains remarkable stability. It is even more stable than the alternative classification method proposed in the literature. These findings emphasise the importance of providing robust results, given the possibility of some margin of error in the weights and parameters of the preference functions, which underlines the reliability and usefulness of the proposed method in strategic decision-making in the sustainable supply chain management.

Finally, it can be concluded that it has contributed to the development of a novel classification method that offers a practical and managerial solution for the segmentation of a large number of customers in the supply chain, standing out for its ability to provide robust and accurate results. Its robustness and easy interpretation by dimensions make it a valuable method that can be added to the DSS and artificial intelligence tools, allowing for the implementation of customised strategies and policies to improve decision-making in sustainable CRM practices in the supply chain.

This method has certain limitations that should be considered. The evaluation criteria integrating the two main dimensions must be well defined and aligned to provide relevant information. Methods such as the Analytic Hierarchy Process can help establish the hierarchies and weights of the criteria within each dimension. There is also a disadvantage in setting a fixed number of groups (four); although, this is an adequate number to establish marketing strategies and is aligned with the average number of groups used in other methods (see Table 1). Moreover, as discussed earlier, the effort required by decision-makers to establish criteria weights and preference functions in PROMETHEE can be cognitively demanding. This method uses a (Type 1) classification, assigning each alternative to a single group, making it unsuitable for contexts where alternatives can belong to multiple groups or remain unclassified.

In future research, it would be interesting to analyse the influence of the number of alternatives on the sensitivity of the final classification and to explore the impact of a third dimension in the evaluation. Additionally, a valuable direction would be to apply this method in other companies, sectors, and supply chain contexts, such as purchasing portfolio models or business-to-consumer models, as well as in domains beyond supply chains, such as education or project evaluation. A comparative analysis with alternative methods in these fields could also provide valuable insights into the method's efficiency and adaptability across diverse contexts.

Supplementary Materials: The following supporting information can be downloaded at https://www.mdpi.com/article/10.3390/math12213427/s1.

Author Contributions: F.B., conceptualization, formal analysis, methodology, and writing—original draft. M.S. and C.M., methodology, supervision, and writing—review and editing. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The datasets presented in this article are not readily available because they are proprietary and contain transactional customer data, which are subject to confidentiality restrictions. Requests to access the datasets should be directed to the corresponding author, subject to organisational approval.

Acknowledgments: The authors thank the company for generously providing the data used in validating the model. We also thank the reviewers for their suggestions to improve the paper.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Pseudo-code of the GLNF matrix classification algorithm

Step 1. Data

Set of alternatives $A = \{a_1, a_2 \ldots, a_i, \ldots, a_n\}$ (customers)

Set of criteria of Dimension 1: $S(D_1) = \left\{s_1, s_2 \ldots, s_j, \ldots, s_m\right\}$ (RFM)

Set of criteria of Dimension 2: $H(D_2) = \left\{h_1, h_2 \ldots, h_j, \ldots, h_n\right\}$ (CC)

Set of criteria weights of Dimension 1: $W^S = \left\{w_1^S, w_2^S \ldots, w_j^S, \ldots, w_m^S\right\}$

Set of criteria weights of Dimension 2: $W^H = \left\{w_1^H, w_2^H \ldots, w_j^H, \ldots, w_m^H\right\}$

Evaluation tables for D_1 and D_2, parameters and weights

Step 2. Global search.

Apply PROMETHEE to the set of alternatives A for both dimensions D_1 and D_2:
Obtain net flows φ_1 for each dimension: $\varphi_1 D_1$ for D_1 and $\varphi_1 D_2$ for D_2
Step 3. Intra-segments local search by dimension.
Perform local searches based on the net flows φ_1, obtaining φ_2:
Apply PROMETHEE to alternatives $\varphi_1 D_1 \geq 0$; results in $+\varphi_2 D_1^{+\varphi_1}$ and $-\varphi_2 D_1^{+\varphi_1}$
Apply PROMETHEE to alternatives $\varphi_1 D_1 < 0$; results in $+\varphi_2 D_1^{-\varphi_1}$ and $-\varphi_2 D_1^{-\varphi_1}$
Apply PROMETHEE to alternatives $\varphi_1 D_2 \geq 0$; results in $+\varphi_2 D_2^{+\varphi_1}$ and $-\varphi_2 D_2^{+\varphi_1}$
Apply PROMETHEE to alternatives $\varphi_1 D_2 < 0$; results in $+\varphi_2 D_2^{-\varphi_1}$ and $-\varphi_2 D_2^{-\varphi_1}$
Where alternatives located at the corners of the matrix go to Step 5:
Upper right corner = Alternatives whose net flows φ_1 and φ_2 are $\geq$0 in both dimensions
Lower left corner = Alternatives whose net flows φ_1 and φ_2 are <0 in both dimensions
Lower right corner = Alternatives whose net flows φ_1 and φ_2 are $\geq$0 in D_1, and φ_1 and φ_2 are <0 in D_2
Upper left corner = Alternatives whose net flows φ_1 and φ_2 are $\geq$0 in D_2, and φ_1 and φ_2 are <0 in D_1
Step 4. Second local search.
Calculate net flows φ_3 by applying PROMETHEE to the less preferred alternatives from the upper subdimension and the more preferred alternatives from the lower subdimension:
Apply PROMETHEE to alternatives $+\varphi_2 D_1^{-\varphi_1}$ and $-\varphi_2 D_1^{+\varphi_1}$; results in $-\varphi_3 D_1$ and $+\varphi_3 D_1$
Apply PROMETHEE to alternatives $+\varphi_2 D_2^{-\varphi_1}$ and $-\varphi_2 D_2^{+\varphi_1}$; results in $-\varphi_3 D_2$ and $+\varphi_3 D_2$
Step 5. Final classification.
Assignment of alternatives to the set of categories $C = \{c_1, c_2, c_3, c_4\}$
Assign alternatives to categories according to their position in the matrix corners (from Step 3):
Assign to C_1 the alternatives located in the upper right corner ($+\varphi_2 D_1^{+\varphi_1}$ and $+\varphi_2 D_2^{+\varphi_1}$)
Assign to C_2 the alternatives located in the upper left corner ($-\varphi_2 D_1^{-\varphi_1}$ and $+\varphi_2 D_2^{+\varphi_1}$)
Assign to C_3 the alternatives located in the lower right corner ($+\varphi_2 D_1^{+\varphi_1}$ and $-\varphi_2 D_2^{-\varphi_1}$)
Assign to C_4 the alternatives located in the lower left corner ($-\varphi_2 D_1^{-\varphi_1}$ and $-\varphi_2 D_2^{-\varphi_1}$)
For alternatives $\varphi_3 \geq 0$, assign them to the adjacent group with the highest preference in the evaluated dimension. On the contrary, for alternatives where $\varphi_3 < 0$, assign them to the adjacent group with the lowest preference in the evaluated dimension.
Assign to C_1 alternatives with $+\varphi_3 D_1$ and $+\varphi_3 D_2$
Assign to C_2 alternatives with $-\varphi_3 D_1$ and $+\varphi_3 D_2$
Assign to C_3 alternatives with $+\varphi_3 D_1$ and $-\varphi_3 D_2$
Assign to C_4 alternatives with $-\varphi_3 D_1$ and $-\varphi_3 D_2$
END

Appendix B

Table A1. Set of variations in indifference and preference thresholds.

Threshold	Recency	Frequency	Monetary	Quota Compliance	Variety of Products	Sustainable Commitment
Indifference	0	0	30	0	0	0
	0	1	20	0	0	0
	0	1	10	0.05	5	0
	0	2	0	0.1	10	0
	0	2	40	0.15	15	0
Preference	0	3	120	0.2	10	0
	0	2	100	0.15	5	0
	0	1	80	0.1	0	0
	0	4	140	0.25	15	0
	0	5	160	0.3	20	0

References

1. Dutta, P.; Jaikumar, B.; Arora, M.S. Applications of data envelopment analysis in supplier selection between 2000 and 2020: A literature review. *Ann. Oper. Res.* **2022**, *315*, 1399–1454. [CrossRef]
2. Ishizaka, A.; Nemery, P. *Multi-Criteria Decision Analysis: Methods and Software*; John Wiley & Sons: Hoboken, NJ, USA, 2013.
3. Baydas, M.; Pamucar, D. Determining Objective Characteristics of MCDM Methods under Uncertainty: An Exploration Study with Financial Data. *Mathematics* **2022**, *10*, 1115. [CrossRef]
4. Ulutas, A.; Krstic, M.; Topal, A.; Agnusdei, L.; Tadic, S.; Miglietta, P.P. A Novel Hybrid Gray MCDM Model for Resilient Supplier Selection Problem. *Mathematics* **2024**, *12*, 1444. [CrossRef]
5. Yenugula, M.; Goswami, S.S.; Kaliappan, S.; Saravanakumar, R.; Alasiry, A.; Marzougui, M.; AlMohimeed, A.; Elaraby, A. Analyzing the Critical Parameters for Implementing Sustainable AI Cloud System in an IT Industry Using AHP-ISM-MICMAC Integrated Hybrid MCDM Model. *Mathematics* **2023**, *11*, 3367. [CrossRef]
6. Yalcin, A.S.; Kilic, H.S.; Delen, D. The use of multi-criteria decision-making methods in business analytics: A comprehensive literature review. *Technol. Forecast. Soc. Chang.* **2022**, *174*, 121193. [CrossRef]
7. Alvarez, P.A.; Ishizaka, A.; Martinez, L. Multiple-criteria decision-making sorting methods: A survey. *Expert Syst. Appl.* **2021**, *183*, 115368. [CrossRef]
8. Barrera, F.; Segura, M.; Maroto, C. Multiple criteria decision support system for customer segmentation using a sorting outranking method. *Expert Syst. Appl.* **2024**, *238*, 122310. [CrossRef]
9. Martinez, R.G.; Carrasco, R.A.; Sanchez-Figueroa, C.; Gavilan, D. An RFM Model Customizable to Product Catalogues and Marketing Criteria Using Fuzzy Linguistic Models: Case Study of a Retail Business. *Mathematics* **2021**, *9*, 1836. [CrossRef]
10. Liu, D.R.; Shih, Y.Y. Integrating AHP and data mining for product recommendation based on customer lifetime value. *Inf. Manag.* **2005**, *42*, 387–400. [CrossRef]
11. Shu, Z.; Carrasco Gonzalez, R.A.; Portela Garcia-Miguel, J.; Sanchez-Montanes, M. Clustering using ordered weighted averaging operator and 2-tuple linguistic model for hotel segmentation: The case of TripAdvisor. *Expert Syst. Appl.* **2023**, *213*, 118922. [CrossRef]
12. Gucdemir, H.; Selim, H. Integrating multi-criteria decision making and clustering for business customer segmentation. *Ind. Manag. Data Syst.* **2015**, *115*, 1022–1040. [CrossRef]
13. De Smet, Y.; Guzmán, L.M. Towards multicriteria clustering: An extension of the k-means algorithm. *Eur. J. Oper. Res.* **2004**, *158*, 390–398. [CrossRef]
14. Segura, M.; Maroto, C. A multiple criteria supplier segmentation using outranking and value function methods. *Expert Syst. Appl.* **2017**, *69*, 87–100. [CrossRef]
15. Segura, M.; Maroto, C.; Segura, B. Quantifying the Sustainability of Products and Suppliers in Food Distribution Companies. *Sustainability* **2019**, *11*, 5875. [CrossRef]
16. Barrera, F.; Segura, M.; Maroto, C. Multicriteria sorting method based on global and local search for supplier segmentation. *Int. Trans. Oper. Res.* **2024**, *31*, 3108–3134. [CrossRef]
17. Miglautsch, J.R. Thoughts on RFM scoring. *J. Database Mark. Cust. Strategy Manag.* **2000**, *8*, 67–72. [CrossRef]
18. Flynn, B.B.; Huo, B.F.; Zhao, X.D. The impact of supply chain integration on performance: A contingency and configuration approach. *J. Oper. Manag.* **2010**, *28*, 58–71. [CrossRef]
19. Casas-Rosal, J.C.; Segura, M.; Maroto, C. Food market segmentation based on consumer preferences using outranking multicriteria approaches. *Int. Trans. Oper. Res.* **2023**, *30*, 1537–1566. [CrossRef]
20. Chen, Y.; Kilgour, D.M.; Hipel, K.W. Multiple criteria classification with an application in water resources planning. *Comput. Oper. Res.* **2006**, *33*, 3301–3323. [CrossRef]
21. Kraljic, P. Purchasing must become supply management. *Harv. Bus. Rev.* **1983**, *61*, 109–117.
22. Marcus, C. A practical yet meaningful approach to customer segmentation. *J. Consum. Mark.* **1998**, *15*, 494–504. [CrossRef]
23. Gelderman, C.J.; Van Weele, A.J. Purchasing Portfolio Models: A Critique and Update. *J. Supply Chain Manag.* **2005**, *41*, 19–28. [CrossRef]
24. Rigopoulos, G.; Askounis, D.T.; Metaxiotis, K. NeXCLass: A decision support system for non-ordered multicriteria classification. *Int. J. Inf. Technol. Decis. Mak.* **2010**, *9*, 53–79. [CrossRef]
25. Goletsis, Y.; Papaloukas, C.; Fotiadis, D.I.; Likas, A.; Michalis, L.K. Automated ischemic beat classification using genetic algorithms and multicriteria decision analysis. *IEEE Trans. Biomed. Eng.* **2004**, *51*, 1717–1725. [CrossRef]
26. Belacel, N. Multicriteria assignment method PROAFTN: Methodology and medical application. *Eur. J. Oper. Res.* **2000**, *125*, 175–183. [CrossRef]
27. Ghanbarizadeh, A.; Heydari, J.; Razmi, J.; Bozorgi-Amiri, A. A purchasing portfolio model for the commercial construction industry: A case study in a mega mall. *Prod. Plan. Control* **2019**, *30*, 1283–1304. [CrossRef]
28. Tchangani, A. Bipolar Fuzzy Nominal Classification (BFNC) framework: Application to risk analysis. *Intell. Decis. Technol. Neth.* **2019**, *13*, 117–130. [CrossRef]
29. Liu, J.; Wang, Y.; Kadzinski, M.; Mao, X.; Rao, Y. A multiple criteria Bayesian hierarchical model for analyzing heterogeneous consumer preferences. *Omega Int. J. Manag. Sci.* **2024**, *128*, 103113. [CrossRef]
30. Rigopoulos, G.; Psarras, J.; Askoun, D.T. A decision support system for supervised assignment in banking decisions. *J. Appl. Sci.* **2008**, *8*, 443–452. [CrossRef]

31. Rigopoulos, G.; Karadimas, N. Multicriteria classification model for student assignment in e-learning modules. *Int. J. Econ. Commer. Manag.* **2022**, *10*, 149–160.
32. Gomez Fama, C.C.; Alencar, L.H. A Classification Model for Managers by Competencies: A Case Study in the Construction Sector. *Math. Probl. Eng.* **2017**, *2017*, 1–16. [CrossRef]
33. Tchangani, A.P. Selectability/Rejectability Measures Approach for Nominal Classification. *J. Uncertain Syst.* **2009**, *3*, 257–269.
34. Amor, S.B.; Belaid, F.; Benkraiem, R.; Ramdani, B.; Guesmi, K. Multi-criteria classification, sorting, and clustering: A bibliometric review and research agenda. *Ann. Oper. Res.* **2023**, *325*, 771–793. [CrossRef]
35. Araz, C.; Ozkarahan, I. Supplier evaluation and management system for strategic sourcing based on a new multicriteria sorting procedure. *Int. J. Prod. Econ.* **2007**, *106*, 585–606. [CrossRef]
36. de Oliveira Silva, L.G.; de Almeida-Filho, A.T. A new PROMETHEE-based approach applied within a framework for conflict analysis in Evidence Theory integrating three conflict measures. *Expert Syst. Appl.* **2018**, *113*, 223–232. [CrossRef]
37. Nemery, P.; Lamboray, C. FlowSort: A flow-based sorting method with limiting or central profiles. *Top* **2008**, *16*, 90–113. [CrossRef]
38. Brans, J.P.; De Smet, Y. PROMETHEE Methods. In *Multiple Criteria Decision Analysis. State of the Art Surveys*; Greco, S., Ehrgott, M., Figuera, J., Eds.; Springer: New York, NY, USA, 2016; Volume 1, pp. 187–219.
39. Rosenfeld, J.; De Smet, Y. An extension of PROMETHEE to hierarchical multicriteria clustering. *Int. J. Multicriteria Decis. Mak.* **2020**, *8*, 133–150. [CrossRef]
40. Barrera, F.; Segura, M.; Maroto, C. PrometheeTools: Promethee and Glnf for Ranking and Sorting Problems. Version 0.1.0; Comprehensive R Archive Network, 2023. [CrossRef]
41. Wickham, H.; Bryan, J.; Posit, P.B.C.; Kalicinski, M.; Valery, K.; Leitienne, C.; Colbert, B.; Hoerl, D.; Miller, E. Readxl: Read Excel Files v1.4.3. Version 1.4.3; Comprehensive R Archive Network, 2023.
42. RStudio. *RStudio: Integrated Development Environment for R v2023.09.1+494*, version 2023.09.1+494; RStudio, PBC: Vienna, Austria, 2021.