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Multiple criteria decision support system for customer segmentation using a sorting outranking method

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ABSTRACT

For companies, customer segmentation plays a key role in improving supply chain management by implementing appropriate marketing strategies. The objectives of this research are to design and validate a multicriteria model to support decision making for customer segmentation in a business to business context. First, the model based on the transactional customer behaviour is extended by a hierarchy with three main criteria: Recency, Frequency and Monetary (RFM), customer collaboration and growth rates. Customer collaboration includes quota compliance, variety of products and customer commitment to sustainability (reverse logistics and shared information). Second, the Global Local Net Flow Sorting (GLNF sorting) algorithm is implemented and validated using real company data to classify 8,157 customers of a multinational healthcare company. Third, the SILS quality indicator has been implemented and validated to assess the quality of preference-ordered customer groups and its parameters have been adapted for contexts with thousands of alternatives. The results are also compared with an alternative model based on data mining (K-means). The multicriteria system proposed allows to segment thousands of customers in ordered categories by preferences according to company strategies. The segments generated are more homogeneous, robust and understandable by managers than those from alternative methods. These advantages represent a relevant contribution to automating supply chain management while providing detailed analysis tools for decision making.

1. Introduction

Supply chain management is a critical factor in ensuring the success of an organisation. In this context, collaboration and effective coordination between the different actors in the supply chain is essential to optimise processes and maximise benefits (Flynn et al., 2010; Cao and Zhang, 2010). Moreover, building collaboration and communication in the supply chain not only results in economic benefits, but also has a positive impact on environmental and social sustainability (Jadhav et al., 2019).

The types of relationships between the links in the supply chain vary according to business models. In the Business-to-Business (B2B) model, companies offer products or services to other companies, in contrast to the Business-to-Customer (B2C) model, where products or services are offered directly to the consumer. Customer Relationship Management (CRM) is crucial for maintaining profitable relationships and creating value for both parties involved (Zhang and Dai, 2020; Soltani and Navimipour, 2016). Segmentation is one of the key axes for implementing a CRM project as it is an important marketing strategy that can help improve profitability and customer relationships (Duarte et al., 2022; Zhang and Dai, 2020; Soltani and Navimipour, 2016). In this sense, segmenting customers facilitates the implementation of targeted marketing and allows companies to adapt their strategies to the specific needs of each segment.

Customer segmentation is based on the assessment of multiple criteria (Maciejewski et al., 2019; Nilashi et al., 2021). Common criteria include demographics (Sarvari et al., 2016), geography and customer behaviour based on purchase transactions (Güçdemir and Selim, 2015) or preferences as measured by opinions about a product or service (Casas-Rosal et al., 2023; Nilashi et al., 2021). On one hand, criteria based on demographics and consumer opinions provide important marketing information in the B2C model (Stormi et al., 2020). On the other hand, in the B2B context, criteria based on purchase quantity, frequency, utility, cost of service, product variety, potential of customer

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growth and loyalty, among others, are used. These criteria are more relevant in the B2B model, where the transactions are larger and the customers are companies with which a long-term relationship is sometimes established. The Recency, Frequency and Monetary (RFM) model is based on the criteria of R, the time elapsed since the last purchase transaction; F, the number of purchase transactions in a time period; and M, the total value of purchase transactions in the same time period (Wei et al., 2010; Miglautsch, 2000). The RFM model is widely used in marketing to classify and segment customers, although it needs to be further developed in some B2B contexts (Stormi et al., 2020).

Traditionally, customer segmentation has been based on data mining techniques (DMi), especially K-means (i.e., Anitha and Patil, 2022; Duarte et al., 2022). However, there are other methods based on Multiple Criteria Decision-Making (MCDM) that also offer efficient segmentations (i.e., Darko and Liang, 2022; Casas-Rosal et al., 2023). Multicriteria methods can help decision-makers (DMs) make decisions considering their preferences in multicriteria contexts where there are one or more conflicting criteria (Ho, 2008). While they have been implemented more to solve supplier evaluation problems (Barrera et al., 2022; Chai & Ngai, 2020; Segura & Maroto, 2017), they are also an alternative in marketing for measuring consumer preference or for modelling consumer behaviour. In consumer behaviour modelling the process begins with market segmentation to identify groups according to different customer needs or characteristics, and then use market targeting to assess the potential interest of each segment for the company (Tsafarakis et al., 2010).

The term classification has different implications depending on the techniques used to group alternatives. On one hand, in MCDM a distinction is made between nominal classification and sorting (ordered groups). In both cases, the DMs oversees the a priori definition or characterisation of the groups into which it seeks to allocate a set of alternatives (Boujelben, 2017). On the other hand, in DMi, classification refers to the supervised prediction of categories from a set of previously classified alternatives, while clustering methods, such as K-means, are unsupervised techniques that generate potential groups in the data, assigning the alternatives to homogeneous categories according to their degree of similarity (De Smet and Montano, 2004).

In marketing, customer segmentation is used to divide a heterogeneous market into several homogeneous markets and can have an a priori or post-hoc approach (Green, 1977). A priori segmentation is performed according to known customer data (purchase quantity, number of clusters, etc.), while post-hoc segmentation is based on the analysis of market data (Han et al., 2014; Liu et al., 2019; Tsafarakis et al., 2010). In marketing, MCDM sorting methods (MCDMS) can be considered as an approach segmentation tool to classify customers into pre-defined segments.

The first objective of this work is to develop a multicriteria system to support decision making in B2B customer segmentation by means of ordered groups. This system is based on a new hierarchy of criteria that extends the RFM model by integrating it with customer collaboration and growth rates, taking into account the company's preferences in its market strategy. The proposed decision support system is called Multicriteria RFM Collaboration (MRFMC) and includes Analytic Hierarchy Process (AHP) for determining the importance of criteria, Preference Ranking Organisation METHod for Enrichment Evaluation (PROMETHEE) and Global Local Net Flow Sorting (GLNF sorting) for customer segmentation and SILhouette for Sorting (SILS) for measuring the quality of allocations. GLNF sorting is based on the concept of net flow and excels in improving the quality of segmentation through local intra- and inter-categorical searches between neighbouring groups.

The second objective is the validation of the model in a B2B empirical case with a very large number of customers, which also allows validation of the algorithm (GLNF sorting) and the quality index (SILS) for this context. To carry out this triple validation, an empirical case has been used in which 8,157 customers of a multinational company that markets health care products in a B2B model are segmented. The results have been compared with an alternative model based on K-means. The quality of the segmentations generated by the system is compared using both SILS and statistical methods.

The main contributions of the work are the extension of the RFM model to MRFMC that includes customer collaboration and supply chain sustainability criteria and the design of a Decision Support System (DSS) that integrates multicriteria techniques and concepts with data mining ideas to generate robust customer segmentations. The validation of GLNF sorting algorithm to segment thousands of customers and the parametric modification of the SILS indicator to measure the quality of assignments in this context provide transparency to process and results, which makes them interesting tools for big data analysis. Validation of the system with real data shows that it can be considered a viable and more robust alternative to traditional clustering techniques used in DMi, allowing companies to both automate decisions and perform detailed analysis to improve their customer relationships, aligning with their collaboration strategies and market approach.

The remainder of this paper is organised as follows: first, a literature review of the RFM model, multicriteria methods for ordered groups and the use of MCDM in customer segmentation is presented. In section three, the methodology of the MCDM techniques used is explained. In section four, the proposed system is detailed and an empirical case is presented for validation. In section five, the results are presented, followed by a discussion of the results in section six. Finally, conclusions are presented in the last section of the paper.

2. Literature review

2.1. RFM model

The RFM model has become a widely used tool in the industry to analyse customer profitability. This model uses the variables R, F and M to assess the transaction behaviour of customers and divide them into five quintiles, from which a ranking score is obtained (Miglautsch, 2000). In segmentation, these scores are used in conjunction with clustering techniques, such as K-means, to identify groups of customers. Subsequently, companies employ group-specific marketing campaign plans (Carrasco et al., 2019).

The RFM model has been integrated with other methods and new variables to extend the approach to other areas such as customer segmentation, customer behaviour and Customer Lifetime Value (CLV) (Wei et al., 2010). This suggests that the RFM model has evolved and adapted to the changing needs of companies to address customer management. Buckinx and Van den Poel (2005) propose models based on DMi to predict partial customer defection, taking into account, among others, the RFM variables. Cheng and Chen (2009) propose a model that links the value of RFM attributes and K-means algorithm into rough set theory. Hosseini et al. (2010) include the B2B concept for together with K-means to achieve classifying customer product loyalty. Zhou et al. (2020) combine RFM analysis with the sparse K-means clustering algorithm for customer segmentation to handle large, high-dimensional and sparse consumer data. Bueno et al. (2021) use RFM variables and integrate them with customer opinion value to evaluate tourism services and rank hotels. Anitha and Patil (2022) propose an RFM model that segments banking customers with K-means to analyse their behaviour and validate the groupings by calculating the silhouette coefficient. Lang et al. (2023) develop a dynamic weighting approach for RFM variables based on big data with the integration of AHP and entropy methods.

MCDM methods have been integrated into RFM models to calculate the importance of variables and segments. For example, Liu and Shih (2005) apply AHP to calculate the weights of criteria R, F and M. Since then, AHP is integrated with RFM to calculate the weight of criteria, obtain ranking of alternatives and segments (i.e., Bueno et al., 2021; Hajmohamad et al., 2021; Moghaddam et al., 2017; Martinez et al., 2021). Fuzzy Analytic Network Process (ANP) has also been used for this purpose (Ravasan and Mansouri, 2015). To determine the a posteriori

Table 1
Evolution of variables in the classical RFM model.

Article	Added criteria	B2B/ B2C	K-means applied?	Application Area
Mahfuza et al. (2022)	Length; volume	B2C	✓	Superstore business
Wu et al. (2022)	Add to cart frequency; Add to favourites frequency	B2C		E-commerce
Hajmohamad et al. (2021)	Profit margins	B2B		Pharmaceutical, sanitary and food products
Zong and Xing (2021)	Cost to service	B2B	✓	Manufacturing industry
Stormi et al. (2020)	The size of the installed base; number parts purchased (part width); money spent on parts (part depth); the fleet service business potential altogether.	B2B		Original equipment manufacturers
Moghaddam et. al (2017)	Variety of products	B2B	✓	Food and sanitary products
Peker et al. (2017)	Length; periodicity	B2C	✓	Retail
Sarvari et al. (2016)	Age; sex	B2C	✓	Insurance
Güçdemir and Selim (2015)	Loyalty; average annual demand; long-term relationship potential; average percentage change in annual demand; average percentage change in annual sales revenue	B2B	✓	Original equipment manufacturers
Wei et al. (2012)	Length	B2C		Health
Chiang (2011)	Discount; Return Cost	B2C		E-commerce

importance of customer segments, Güçdemir and Selim (2015) use Fuzzy AHP, while Mahdiraji et al. (2019) apply the Best Worst Method (BWM) and COmplex PRoportional ASesment (COPRAS) methods.

Research using the RFM model with new criteria to segment customers in B2C and B2B models can be found in Table 1. The use of the K-means algorithm as a clustering method to obtain the segments is also highlighted.

There are other customer segmentation models focused on B2C that are based on demographic criteria, product/service characteristics and consumer preference measurement. For example, in food products one can find price, nutritional information, geographical origin, retailer brand, type of packaging, among others (i.e., Casas-Rosal et al., 2023; Maciejewski et al., 2019). In hospitality the customer's opinion regarding: location, sleep quality, cleanliness, room, service, value, and check-in/front desk (Nilashi et al., 2021; Ahani et al., 2019; Nilashi et al., 2019). In the Automotive sector, price, max speed, fuel consumption and acceleration have been used (Liu et al., 2019). To model customer satisfaction in financial mobile services, criteria such as interface, system update, verification, customer support, system functionality, among others, have been considered (Darko and Liang, 2022). Demographic and psychographic criteria according to Andrews et al. (2010) have been applied by service providers to segment customers in companies.

Although collaborative supply chains have been recognised as having advantages for improving firm performance (Flynn et al., 2010; Cao and Zhang, 2010), no additional variables proposed to the RFM model have been applied to segment customers and directly assess their collaboration in a B2B model. In this research we propose a hierarchy of criteria focusing not only on transactional behaviour, but also on customer collaboration, assessing compliance with purchase quotas, commitment to sustainability and variation in the types of products demanded. This research will also contribute to the sustainability focus on the literature by considering reverse logistics collaboration and information sharing to improve sustainable sourcing, aspects that have not been integrated into RFM models of customer segmentation.

2.2. Multicriteria sorting problem and PROMETHEE-based methods

The sorting problem consists of assigning alternatives to ordered categories, previously characterised by the DMs or inherent to the problem. Methods to solve this problem fall into four categories: outranking approach, full aggregation approach, goal aspiration or reference-level and non-classical approach (Alvarez et al., 2021). Outranking approach is based on non-compensatory multicriteria techniques, where the loss of score in one criterion cannot be compensated

Table 2
MCDM in customer classification, sorting and clustering.

Article	Application Area	Type aggregation	Based on	Type techniques	K-means applied?	MCDM method	MCDM objective
Casas-Rosal et al. (2023)	Food	Nominal classification and sorting	CPM	MCDM		PROMETHEE II; FlowSort extension	Customer classification and sorting
Darko and Liang (2022)	Financial mobile services	Clustering and sorting	CPM	MCDM and DMi		PLGD-FlowSort	Sorting of customers preferences
Nilashi et al. (2021)	Hotel	Clustering	CPM	MCDM and DMi		Entropy-weight approach	Importance of criteria
Martinez et al. (2021)	Retailers	Clustering	CTB	MCDM and DMi	✓	AHP	Importance of criteria and products to define segments
Mahdiraji et al. (2019)	Financial services	Clustering	CTB	MCDM and DMi	✓	BWM; COPRAS	Importance of segments
Liu et al. (2019)	Automotive	Clustering	CPM	MCDM and DMi		New method (additive value function)	Customer preferences for segmentation
Ahani et al. (2019); Nilashi et al. (2019)	Hotel	Clustering	CPM	MCDM and DMi		TOPSIS	To rank criteria for each defined segment
Güçdemir and Selim (2015)	Electronic manufacturing	Clustering	CTB	MCDM and DMi	✓	Fuzzy AHP	Importance of segments
Ravasan and Mansouri (2015)	Auto insurance	Clustering	CTB	MCDM and DMi	✓	Fuzzy ANP	Importance of criteria
Liu and Shih (2005)	Hardware retailing	Clustering	CTB	MCDM and DMi	✓	AHP	Importance of criteria

Note: PLGD (Probabilistic Linguistic Group Decision); Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS).

Table 3
Table of customer evaluation and limiting profiles of ordered groups.

Customers and limiting profiles	$g_1(\cdot)$ w_1	…	$g_j(\cdot)$ w_j	…	$g_m(\cdot)$ w_m
Cu_1	$g_1(Cu_1)$	…	$g_j(Cu_1)$	…	$g_m(Cu_1)$
⋮	⋮	…	⋮	…	⋮
Cu_i	$g_1(Cu_i)$	…	$g_j(Cu_i)$	…	$g_m(Cu_i)$
⋮	⋮	⋱	⋮	⋱	⋮
Cu_n	$g_1(Cu_n)$	…	$g_j(Cu_n)$	…	$g_m(Cu_n)$
r_1	$g_1(r_1)$	…	$g_j(r_1)$	…	$g_m(r_1)$
⋮	⋮	⋱	⋮	⋱	⋮
r_{k+1}	$g_1(r_{k+1})$	…	$g_j(r_{k+1})$	…	$g_m(r_{k+1})$

by the gain in another criterion, and it is possible that two alternatives with similar scores are incomparable (Ishizaka & Nemery, 2013).

PROMETHEE-based sorting methods have been developed in the literature that allocate a set of alternatives $A = \{a_1, a_2, \cdots, a_i, \cdots, a_n\}$ evaluated with a set of criteria $G = \{g_1, g_2, \cdots, g_j, \cdots, g_m\}$ to different classes by comparing them with the limiting profiles $R = \{r_1, r_2, \cdots, r_h, \cdots, r_{k+1}\}$ that predefine them (De Smet and Montano, 2004). Araz and Ozkarahan (2007) presented PROMETHEE Sorting (PROMSORT), which uses partial ranking to assign alternatives into ordered groups. In this method an alternative may be incomparable or indifferent with respect to a limiting profile. Nemery and Lamboray (2008) proposed FlowSort, which uses a full ranking to classify one alternative at a time, comparing it to the limiting profiles through its net flow. This method requires applying PROMETHEE for each of the alternatives, which complicates its implementation when the number of alternatives is very large. Silva and de Almeida-Filho (2018) developed β-PROMETHEE, a classification approach that analyses the Dempster-Shafer Theory conflict. On the other hand, Barrera et al. (2023) have proposed the GLNF sorting algorithm, based on net flows in global and local searches. In contrast to PROMSORT, GLNF sorting achieves complete classification and better discrimination between alternatives that lie on the border of two neighbouring groups. Furthermore, unlike FlowSort, GLNF sorting not only uses predefined limiting profiles for the groups, but also considers clustering according to the degree of preferential similarity between alternatives, providing more systematic classification.

PROMETHEE has also been considered in multicriteria clustering problems where the clusters are not known in advance. De Smet et al. (2012) propose an algorithm that generates ordered clusters based on the definition of an inconsistency matrix and using only the ordinal information of the preference relations between pairs. Sarrazin et al. (2018) present a clustering model based on PROMETHEE I that allows alternatives to be assigned to individual or interval clusters. Rosenfeld and De Smet (2020) propose the use of net flows to create ordered clusters, following a hierarchical approach. Bai et al. (2019) propose an algorithm based on fuzzy c-means and net flow. Other studies have used adaptations of K-means to integrate PROMETHEE preferences (De Smet and Montano, 2004; Chen et al., 2018). Pereira et al. (2022) applied an ordered clustering model to countries according to the Health Security Index, and in contrast to the provider assessment context addressed by Barrera et al. (2023), in this case they do not consider it necessary to assign alternatives to a specific cluster when they were between the boundaries of two groups.

2.3. Multicriteria methods in customer segmentation

Table 2 shows publications focusing on customer segmentation using models that integrate at least one MCDM method. It is indicated whether the type of aggregation of the model is based on clustering or on a nominal or sorting type MCDM classification. It also describes whether the classifications or clustering are based on customer preference measurement (CPM) or customer transactional behaviour (CTB). It is observed that most of the research models are hybrid, suggesting that these approaches could be the future of the use of MCDM methods for classification, sorting and clustering (Amor et al., 2022).

MCDM techniques have been used primarily to determine the importance of criteria or customer segments, while clustering is done using DMi techniques, such as the K-means algorithm. AHP has been applied to determine the weighting of criteria in several investigations (see Table 2). However, the use of MCDM in the literature to classify customers is limited. Darko and Liang (2022) developed the PLGD-FlowSort model to measure customer satisfaction, while Casas-Rosal et al. (2023) applied an extension of FlowSort to perform the sorting and proposed a nominal classification based on PROMETHEE II.

In conclusion, the use of MCDMS has been based on models using consumer behaviour and therefore B2C models. In general, the literature review confirms that the use of clustering techniques such as K-means is more popular in customer segmentation models, as mentioned by Ernawati et al. (2021). On the other hand, the use of MCDM has been restricted to the prioritisation of criteria and segments after classification with a clustering method. This research fills this gap in the literature by proposing a customer segmentation model based on MCDMS by extending the use of the GLNF sorting algorithm proposed by Barrera et al. (2023). Although this algorithm has been tested in a real case of supplier segmentation, it has not yet been validated on customer classification or on problems with a large number of alternatives.

3. Methodology

This section presents the multicriteria methods on which the proposed DSS integrating AHP, PROMETHEE, GLNF sorting and SILS is based.

3.1. The AHP method

This method is widely used in the literature to calculate the weights of the evaluation criteria. The calculation of the weight of the criteria with AHP can be done with the following steps (Saaty, 1980; Saaty and Peniwati, 2008):

1) Hierarchy criteria: The set of evaluation criteria is identified $G = \{g_1, g_2, \cdots, g_j, \cdots, g_m\}$ and their hierarchy structure.
2) Comparison matrix: The criteria comparison matrix *m* x *m* is constructed using the direct comparison between each pair of criteria. The pairwise comparison is carried out by the DMs using the Saaty scale.
3) Consistency: The consistency of the comparisons made with DMs' value judgements is checked. A consistency index is calculated and compared with a random consistency index.
4) Weights: Criteria weights are calculated using the eigenvector method. The set of criteria weights being $W = \{w_1, w_2, \cdots, w_j, \cdots, w_m\}$.

If the comparison matrix made by the DMs is consistent, it can be integrated with other consistent matrices through the geometric averaging mean, favouring collaborative decision-making.

3.2. The PROMETHEE method

PROMETHEE is based on the principle of preference, which is obtained through a two-way pairwise comparison of the alternatives for each of the criteria evaluated. At Table 3 the evaluation table for the set of alternatives is presented *Z*, made up of the sum of the set of customers $A = \{Cu_1 Cu_2, \cdots, Cu_i, \cdots, Cu_n\}$ and the set of limiting profiles $R = \{r_1, r_2, \cdots, r_h, \cdots, r_{k+1}\}$. The limiting profiles define the *K* ordered segments in the classification methods. The evaluation criteria are defined as $G = \{g_1, g_2, \cdots, g_j, \cdots, g_m\}$ and their associated weighting as $W =$

$\{w_1, w_2, \cdots, w_j, \cdots, w_m\}$.

The first step in the PROMETHEE method is to define a preference function for each criterion, in order to eliminate the scale effect and obtain a preference between the two-way pairwise comparison F_j for each criterion. For this purpose, the deviation d_j between each pair of alternatives Cu_i and Cu_q is calculated for each criterion g_j as shown in equation (1). It is then converted to preference using equation (2), on a scale of [0, 1] (equation (3)), where a value of 1 indicates absolute preference:

$$d_j(Cu_i, Cu_q) = g_j(Cu_i) - g_j(Cu_q), \tag{1}$$

$$P_j(Cu_i, Cu_q) = F_j[d_j(Cu_i, Cu_q)], \tag{2}$$

$$0 \le P_j(Cu_i, Cu_q) \le 1. \tag{3}$$

The DMs can choose different preferred functions according to the needs of the company, e.g. linear functions with and without indifference threshold, and functions of the usual type. In linear functions with the indifference threshold q it is defined that $q > 0$ and p strict preference threshold. If $d_j(Cu_i, Cu_q) \le q$, then $P_j(Cu_i, Cu_q) = 0$. If $d_j(Cu_i, Cu_q) > q$, then $P_j(Cu_i, Cu_q)$ increases linearly with slope as follows: $1/(p-q)$. If $d_j(Cu_i, Cu_q) \ge p$, then $P_j(Cu_i, Cu_q) = 1$. For functions of the usual type, where $d_j(Cu_i, Cu_q) > 0$, therefore a strict preference $P_j(Cu_i, Cu_q) = 1$.

Once the preference function has been defined P_j, the Aggregated Preference Index (API) is calculated for each pair of alternatives in the set Z. API between the alternatives Cu_i and Cu_q is calculated using the following equation:

$$\pi(Cu_i, Cu_q) = \sum_{j=1}^{m} P_j(Cu_i, Cu_q) \cdot w_j. \tag{4}$$

The positive outranking flow is calculated using equation (5), and represents the extent to which one customer outperforms the others. On the other hand, the negative outranking flow is calculated in equation (6) and indicates the extent to which a customer is outperformed by other customers. Both flows are used to obtain a partial ranking of alternatives (PROMETHEE I). To achieve a full ranking (PROMETHEE II), it is necessary to calculate the net flow as shown in equation (7). Both the positive and negative outranking flows and the net flow are basic concepts used by other methods to classify alternatives. For example, the GLNF sorting algorithm, validated in this research, is based on the signs of the net flow. The net flow of an alternative is also the scalar product between the vector of weights and the profile vector of this alternative (equation (8)). More details on the PROMETHEE method can be found in Brans & De Smet, 2016:

$$\varphi^+(Cu_i) = \frac{1}{n-1} \sum_{x \in Z} \pi(Cu_i, x), \tag{5}$$

$$\varphi^-(Cu_i) = \frac{1}{n-1} \sum_{x \in Z} \pi(x, Cu_i), \tag{6}$$

$$\varphi(Cu_i) = \varphi^+(Cu_i) - \varphi^-(Cu_i), \tag{7}$$

$$\varphi(Cu_i) = \sum_{j=1}^{m} \varphi_j(Cu_i) \cdot w_j. \tag{8}$$

3.3. The GLNF sorting method

GLNF sorting is a method proposed by Barrera et al. (2023) to classify alternatives into ordered groups, categories, or segments. This method is based on the fact that alternatives with positive net flows obtained with PROMETHEE II are strongly preferred over the rest (Rosenfeld and De Smet, 2020) and on further local intra- and inter-category searches that improve the quality of the alternatives' group assignments.

The GLNF sorting method consists of five steps, which are described below:

1) Data: K segments are defined along with their preferred order, denoted as $C1 \succ C_2, \cdots, \succ C_h, \cdots, \succ C_k$. A multicriteria evaluation table is also defined that includes the set of alternatives (customers) $A = \{Cu_1, Cu_2, \cdots, Cu_i, \cdots, Cu_n\}$ and the set of limiting profiles $R = \{r_1, r_2, \cdots, r_h, \cdots, r_{k+1}\}$. Each segment C_h is defined between two limiting profiles: the higher r_h and the lower r_{h+1}. The higher limit of C_1 is r_1 which represents the best possible value that can be assigned to each criterion, while the lower bound of C_k is r_{k+1} which represents the worst possible value that can be assigned to each criterion.
2) Global search: PROMETHEE is applied to the datasets A and R to obtain the values of the net flows (φ_1) and form a ranking. Customers are pre-classified according to their net flow position, φ_1, and the position of the φ_1 of the limiting profiles defining each segment, following the rule: if $\varphi_1(r_h) > \varphi_1(Cu_i) \ge \varphi_1(r_{h+1})$, then $Cu_i \in C_h$. However, if $\varphi_1(Cu_i) = \varphi_1(r_1)$, then $Cu_i \in C_1$.
3) Intra-segment local search: PROMETHEE is calculated to obtain the net flows (φ_2) of customers in each of the segments defined in the previous step. That is, PROMETHEE k number of times. Then, according to the sign of the φ_2 the customers are divided in each segment C_h into two subgroups: the preferred ones with φ_2 positive or zero ($+\varphi_2(C_h)$) and non-preferred with φ_2 negative ($-\varphi_2(C_h)$).
4) Inter-segment local search: Using the information from the previous step, the net flows (φ_3) are calculated by applying PROMETHEE to the non-preferred customers of the segment C_h with the outcome $-\varphi_2(C_h)$ and to the preferred customers of the lower neighbouring segment C_{h+1} that obtained $+\varphi_2(C_{h+1})$. This step does not apply for the most preferred customers in the segment C_1 with $+\varphi_2(C_1)$, nor for the least preferred customers in the segment C_k with $-\varphi_2(C_k)$, these move directly from step three to step five because, being at the extremes, they do not have a neighbouring group to search for, so they are definitively classified into C_1 and C_k respectively. Thus, the number of PROMETHEE applications for this local search is $K-1$, once for each neighbouring pair of segments.
5) Final allocation of customers: According to the signs of the φ_3 calculated in the second local search, the final allocation is made. Customers with positive or zero φ_3 are assigned to the most preferred group C_h while customers with negative φ_3 are assigned to the least preferred segment C_{h+1}.

The visual representation of the algorithm steps is presented in Fig. 2 with the results of its implementation in the B2B empirical case of this research.

3.4. Silhouette for sorting (SILS)

The SILS is an index proposed by Barrera et al. (2023) to measure the quality of alternative (customer) allocations in ordered groups, based on PROMETHEE net flows. It can be considered as a silhouette extension presented in Rousseeuw (1987) for clustering.

In order to apply SILS, it is required to have the classification data, which includes the customer of the set $A = \{Cu_1, Cu_2, \cdots, Cu_i, \cdots, Cu_n\}$ and its classification into the ordered segments $C_1 \succ C_2, \cdots, \succ C_h, \cdots, \succ C_k$ which were predefined by the set of limiting profiles $R = \{r_1, r_2, \cdots, r_h, \cdots, r_{k+1}\}$. Subsequently, PROMETHEE is applied to the sets A and R to calculate the net flows of the customers and limiting profiles. The net flows of the limiting profiles are used to calculate the centroid E_h of the segment C_h, as shown in equation (9):

$$E_h = \frac{\varphi r_h + \varphi r_{h+1}}{2}. \tag{9}$$

Subsequently, the average dissimilarity of the i customer is calculated

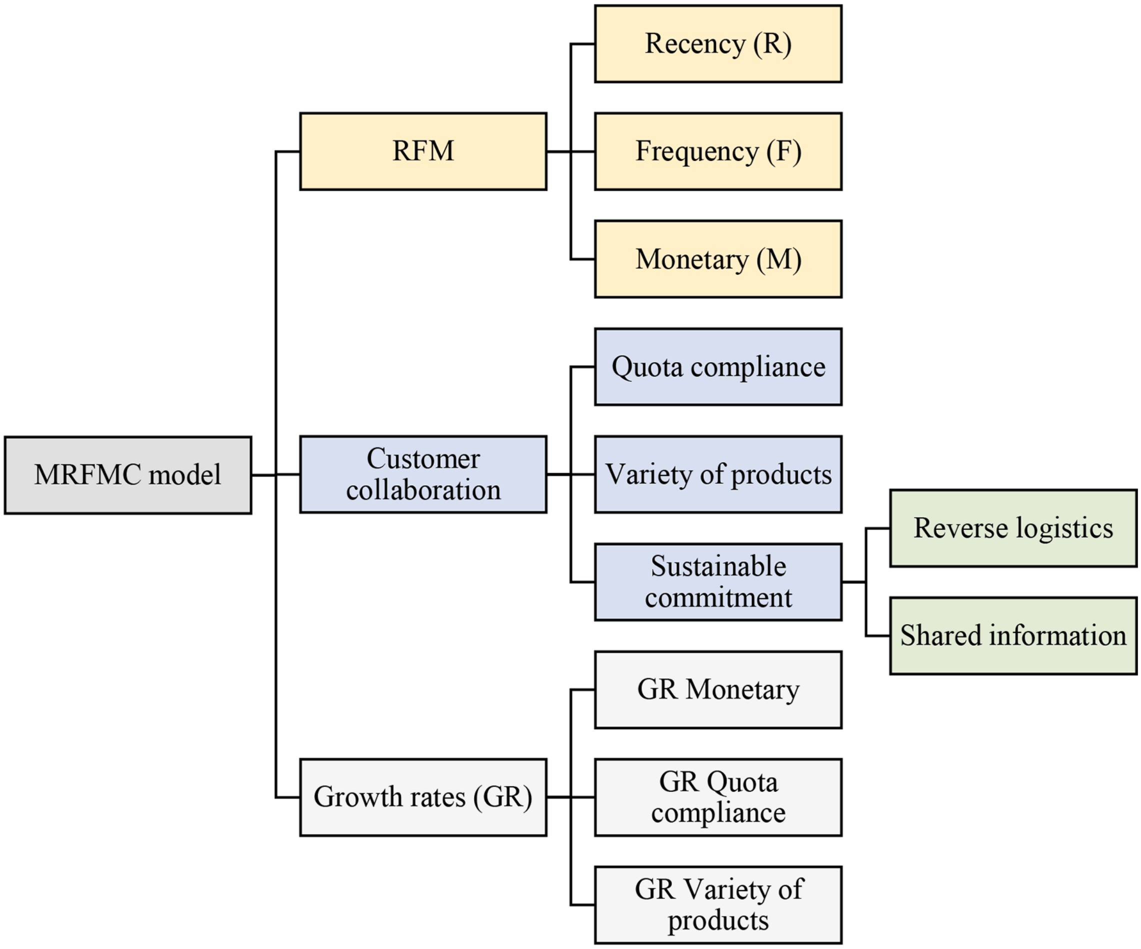

Fig. 1. Hierarchy of the evaluation criteria for customer classification.

with respect to the N customers that make up the current segment C_h, the higher neighbouring segment C_{h-1} and the lower neighbouring segment C_{h+1}. These average dissimilarities are represented as $u(i)$, $h(i)$, and $l(i)$ respectively, in equations (10), 11 and 12. Finally, these dissimilarities are used to calculate SILS(i) in equation (13):

$$u(i) = \frac{\left(\sum_{Cu_j \in C_h} \left|\varphi(Cu_i) - \varphi(Cu_j)\right|\right) + |\varphi(Cu_i) - \varphi(E_h)|}{N_h}, \tag{10}$$

$$h(i) = \frac{\left(\sum_{Cu_j \in C_{h-1}} (\varphi(Cu_j) - \varphi(Cu_i))\right) + (\varphi(E_{h-1}) - \varphi(Cu_i))}{N_{h-1} + 1}, \tag{11}$$

$$l(i) = \frac{\left(\sum_{Cu_j \in C_{h+1}} (\varphi(Cu_i) - \varphi(Cu_j))\right) + (\varphi(Cu_i) - \varphi(E_{h+1}))}{N_{h+1} + 1}, \tag{12}$$

$$\mathrm{SILS}(i) = \frac{l(i) - u(i)}{\max(l(i), u(i))} - \frac{h(i) - u(i)}{\max(h(i), u(i))}. \tag{13}$$

The value of SILS(i) is on the scale $(-2, 2)$, with an approximate value of -2 when $l(i) \ll u(i) \ll h(i)$, approximately 2 when $l(i) \gg u(i) \gg h(i)$, and around 0 when $l(i) \gg u(i) \ll h(i)$. To interpret the SILS(i) values, the authors suggest dividing the scale into three parts, e.g. by setting control limits at -1 and 1. Values below -1 indicate that the customer i could be better classified in the lower neighbouring segment, values above 1 indicate that the customer i could be better classified in the higher neighbouring segment, and values between -1 and 1, indicate that the customer i is well classified in its current segment.

It is important to note that if the customer $i \in C_1 \rightarrow h(i) = d_0 \vee i \in C_k \rightarrow l(i) = d_{k+1}$, where d_0 and d_{k+1} are fictitious average dissimilarities that replace the values of $h(i)$ and $l(i)$ respectively. This is due to the non-existence of an upper neighbour group of C_1 and a lower neighbouring group of C_k. Given the case that $d_0 = d_{k+1}$, then one will have only one average dissimilarity named d_t. Authors Barrera et al. (2023) justify a $d_t = 100$ to avoid considering a SILS value that favours the reallocation of an alternative to a non-existent segment.

Finally, although the SILS values are calculated per alternative, it is possible to have an overall measure of the group and of the whole classification technique by averaging the absolute SILS value of the alternatives in the same group or of all alternatives.

4. New model for customer segmentation

4.1. The MRFMC model

This section describes the proposed procedure for classifying customers into ordered groups. The business model approach addressed is B2B, and in some cases is also applicable for B2C. The steps to implement the model are presented below:

Step 1: Problem definition and scope. The set of customers, the number and preference of groups, the evaluation time period, products or services and the experts who will define the parameters of the model are established.

Step 2: Pre-processing of data and calculation of indicators to measure the criteria. In this step, the database is extracted, reviewed and adjusted to organise it and identify errors. The aim is to obtain the evaluation table for all customers. Fig. 1 illustrates the hierarchy of evaluation criteria encompassing three dimensions grounded in customer behaviour. This hierarchical structure is derived from an analysis of the literature review and insights from expertise of managers engaged in the research. The first dimension is RFM criteria, universally acknowledged in the literature as pivotal elements for scrutinising customer transactional behaviour for segmentation purposes (Anitha and Patil, 2022; Zhou et al., 2020; Wei et al., 2012; Hosseini et al., 2010; Cheng and Chen, 2009; Miglautsch, 2000). R is the time elapsed since the last purchase and the date on which the model is run; F represents the number of purchase transactions in the evaluation period; and M is the total value of purchases made (monetary) by a customer during the evaluation period T which is defined as M_T. The objective is to minimise R and maximise F and M.

In addition to the RFM criteria, the hierarchy has been enriched with two other dimensions. The second dimension measures the level of customer collaboration in a B2B business model, allowing for more comprehensive assessments by considering the maximisation of criteria such as quota compliance, product variety and sustainable commitment. Although the literature highlights the benefits of collaboration in the supply chain (Jadhav et al., 2019; Flynn et al., 2010; Cao and Zhang, 2010), its implementation in customer segmentation systems has not been fully developed. Therefore, its incorporation to hierarchy is deemed a pertinent addition to the suggested framework, particularly within B2B models where suppliers assume a leadership role in relationship management.

Quota compliance (QC) refers to the percentage of a customer's compliance Cu_i with respect to the minimum quota or quantity they committed to purchase, calculated in equation (14), where M_{qT} is the purchase quota. The literature review reveals that this criterion has not been integrated into RFM customer segmentation models. However, business experts indicate this criterion is relevant in models with trade marketing strategies, where the business grants benefits to customers who meet purchase quotas:

$$QC(Cu_i) = \left(\frac{M_T}{M_{qT}}\right)\cdot 100\%. \tag{14}$$

Variety of products (VP), which indicate the number of distinct product types a customer purchases within a specific timeframe, has been employed in the literature to attain a finer understanding and categorisation of customer behaviour in B2B models (Moghaddam et. al, 2017). This notably pertinent criterion has been integrated into the suggested hierarchy, albeit with a more comprehensive methodology. The proposed VP criterion measures the proportional share of purchases of different product varieties or brands by a customer, and compares them to the ideal proportional share defined by the enterprise. This criterion seeks to assess both the diversity of products purchased by a customer and the monetary importance of these products in the purchases. It is important for companies to promote the marketing of their product portfolio in the desired proportions, e.g. by prioritising the positioning of those products that are more profitable or that target a new target market.

Equation (15) represents a customer's VP calculation Cu_i. It is defined on the scale [0, 100], where M_{TP_j} is the total amount of the product purchased $j(P_j)$ in the period T, and W_{P_j} is the ideal proportional share as defined by the firm for P_j. For example, if a P_j has an importance of 30 % ($W_{P_j} = 0.3$), and a customer has made purchases of \$500, of which \$100 is for the purchase of P_j then the actual share of the purchase of P_j will be 20 % and the VP value for this product will be 20 points. However, if the purchase share is 30 % or more, then a score of 30 is awarded:

$$VP(Cu_i) = \sum_{j=1}^{n} \min\left(\frac{M_{TP_j}}{M_T},\ W_{P_j}\right)\cdot 100. \tag{15}$$

The last criterion of the customer collaboration dimension assesses commitment to sustainability. Its incorporation is substantiated by the growing importance of sustainability in the supply chain, according to the literature (Van Belle et al., 2021; Zhao et al., 2018; Khan et al., 2016). Nonetheless, its explicit role as an evaluation criterion in customer segmentation has remained relatively restricted. Thus, its inclusion serves to bridge this gap and address an overlooked criterion in conventional customer segmentation models. Sustainable commitment is divided into two key sub-criteria: reverse logistics and shared information. Reverse logistics is essential to ensure the proper disposal of discarded products, especially in the case of pharmaceuticals and cosmetics, where improper recycling can put people's health at risk. It also allows the recovery of useful materials and components from discarded products, which can reduce the need to extract new raw materials. The information that the customer shares with the enterprise is relevant to contribute to greater sustainability in sourcing, decreasing the resources allocated to excess inventories and overproduction (Khan et al., 2016). The sub-criteria are qualitative, so it is proposed to measure them on an ordinal scale of 1 to 5, where five represents excellent collaboration and one represents poor collaboration (see appendix A).

The last dimension focuses on assessing and maximising the variation of criteria between the time periods $T-1$ and T. Based on Table 1, growth rates (GR) that measure variations for demand and monetary criteria were introduced by Güçdemir and Selim (2015). The significance of these GR lies in their simple assessment of customer behaviour over time. Hence, in addition to the monetary GR, growth rates for QC and VP criteria have been incorporate, integrating them into the GR axis. This integration serves to represent such behaviour and improve the interpretation of the overall results by managers. The variations between the last two years are considered to identify growth, decline or stagnation of customers (being zero for customers less than two years old). For example, the monetary GR indicates whether the purchases of a customer Cu_i have increased (positive rate), decreased (negative rate) or remained unchanged (zero rate). Equation (16) represents the calculation of GR monetary, where the M_{T-1} is the amount of purchases in the previous period. The variations of the other two criteria are calculated in a similar way:

$$GR\ monetary(Cu_i) = \left(\frac{M_T - M_{T-1}}{M_{T-1}}\right)\cdot 100\%. \tag{16}$$

Step 3: Definition of criteria weights. Weights are obtained through the application of AHP by the DMs, experts and/or analysts. With the geometric mean, the individual matrices are aggregated to obtain consensus matrices and weights.

Step 4: PROMETHEE preference functions and limiting profile values that define customer categories or segments are established.

Step 5: Customer classification. The GLNF sorting algorithm is run to obtain the ordered customer classification.

Step 6: Analysis of the results. The classification quality index is calculated for each customer using the SILS method to measure the quality of the assignments.

4.2. MRFMC model validation: customer classification in a real consumer packaged goods industry

Step 1: The proposed model was validated using real data from a multinational company that manufactures consumer packaged goods, pharmaceuticals products, and medical devices. Consumer packaged goods are focused on health care, for example, oral health, skin care, baby care, among others. In Colombia, the market for this type of product is highly competitive, and the company applies a B2B business model with the development of trade marketing strategies to increase sales and product positioning. Due to the limited resources and the number of customers, it is necessary to focus the company's efforts on customers with the greatest potential. This requires a multicriteria a priori segmentation approach that classifies customers into groups based on their behaviour and prioritises (orders) these groups according to the

Table 4
Weights of criteria in the customer classification.

Dimension	Criterion	% Global Weight
RFM	Recency	3.87
	Monetary	35.05
	Frequency	10.13
Customer collaboration	Quota compliance	5.17
	Variety of products	23.84
	Sustainable commitment	2.18
Growth rates	GR Monetary	11.15
	GR Quota compliance	1.51
	GR Variety of products	7.10

company's value judgements. Actually, the company classifies its customers without using any MCDM techniques based on only two criteria: the value of sales and the customer's interest in promoting the products.

Data has been pre-processed in Microsoft Excel to classify 8,157 customers, distributed in Colombia throughout the country, into four ordered groups $C_1 \succ C_2 \succ C_3 \succ C_4$ (no customer has been previously classified). These customers purchase products from a catalogue of 21 brands marketed by the company, ranging from personal care products for adults and babies to over-the-counter medicines, cosmetic creams and others. The data are for two annual periods, with the main assessment year being 2022 (T). The criteria of frequency and recency are measured in months for T. The definition of the model parameters has been carried out by a sales executive and an analyst.

Step 2: The data of the 8,157 customers have been processed and verified in order to obtain the evaluation table with the criteria of the Fig. 1. As the company is at an early stage in its sustainability assessment with its customers, hypothetical data was used for the sustainable commitment criterion. In addition, a division of the values of the customers' annual purchases by a factor was applied to ensure confidentiality of the data.

Step 3: Table 4 shows the definition of the global weights of the criteria and their dimensions. The RFM dimension has a weight of 49.05 %, where the monetary criterion has the highest overall weight with 35.05 %. The criteria of the customer collaboration dimension have an important weight of 31.19 %, with variety of products being the most relevant with an overall weight of 23.84 %. The last dimension growth rates has a weight of 19.76 %, with GR monetary being the criterion with the highest overall weight with 11.15 %.

Step 4: Both the five limiting profiles used to define the ordered groups and the parameters of the preferred functions have been established taking into account the evaluation table and the company's preferences. Recency is the only criterion that is minimised. The monetary criterion is defined by a linear function, in which the threshold of indifference is 30 and the preference threshold is 120. This means that, among customers with a purchase difference equal to or less than 30, there will be no preference. Preference will increase linearly when the difference between the purchases of two customers is between 30 and 120, and there will be an absolute preference for the customer who has purchased the most when this difference is equal to or greater than 120.

On the other hand, sustainable commitment is defined qualitatively, so that a usual preference function is established where any difference between the integers on the scale marks an absolute preference for the highest value customer. The other criteria are measured with linear preference functions without an indifference threshold. For the recency criterion a preference threshold of one month is set, for frequency of three months and for variety of products its value is 10. In quota compliance a preference threshold of 20 % is set, while in the GR monetary, GR variety of products and GR quota compliance criteria the preference thresholds are 10 %, 14 % and 10 % respectively.

5. Results

5.1. Customer segmentation

Calculations of PROMETHEE net flows have been obtained with D-sight CDM (2023) software and Statgraphics Technologies (2018) has been used to represent the results graphically and perform statistical analyses.

In Fig. 2 the classification results for each of the five steps of the GLNF sorting algorithm appear. In the first step, the required data are the evaluation table of all customers and the profiles defining the segments. In the second step, PROMETHEE is applied and according to the values of the net flow φ_1, 926 customers are pre-classified into C_1, 2,295

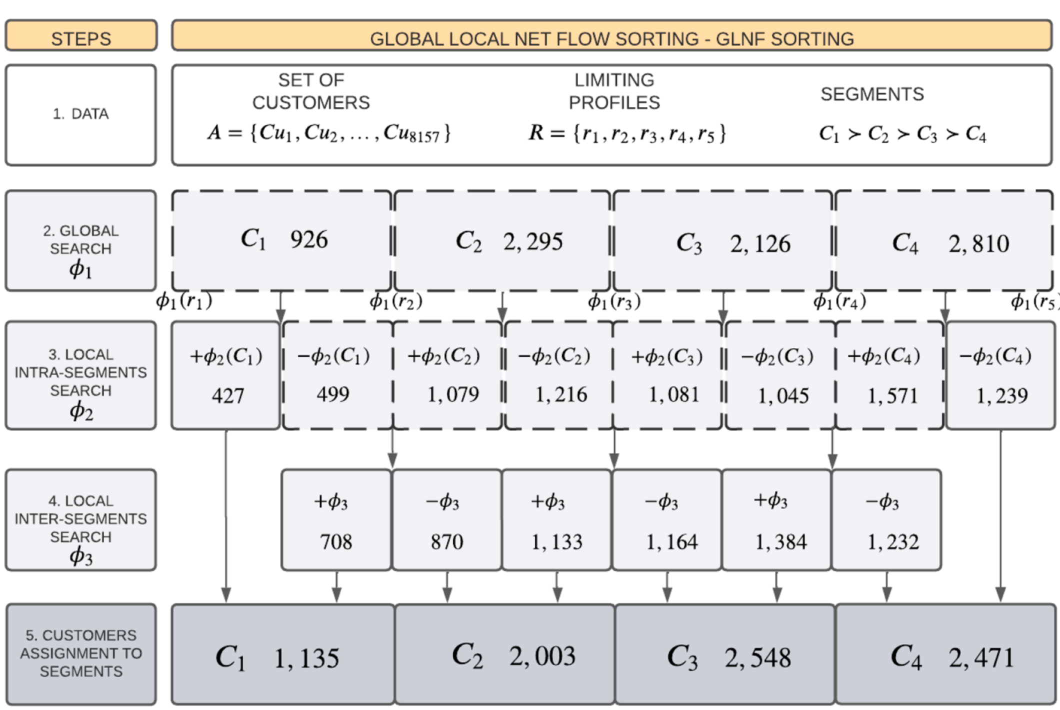

Fig. 2. Customer classification with GLNF sorting.

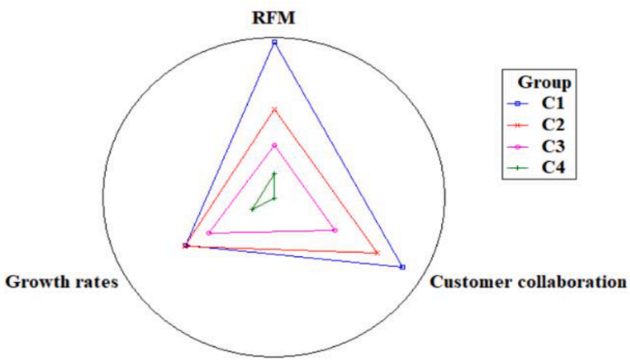

Fig. 3. Average net flow from global search by criteria dimension and segment.

in C_2, 2,126 in C_3 and 2,810 in C_4. In the third step, a local search is carried out in each of the segments, whose net flow is φ_2. Thus, by applying PROMETHEE to 2,295 customers pre-classified in C_2, then 1,079 customers with a positive net flow are distinguished $+\varphi_2(C_2)$ and 1,216 customers with negative net flow $-\varphi_2(C_2)$. Overall, the former are preferred to the latter. In the fourth step, PROMETHEE is applied in an inter-segment search to the least preferred customers of one segment and to the most preferred customers of the neighbouring segment below. For example, the inter-segment search is carried out between the 1,216 customers of C_2 with negative net flows $-\varphi_2(C_2)$ and the 1,081 customers of C_3 with positive net flows $+\varphi_2(C_3)$, resulting in 1,133 customers with positive net flows $+\varphi_3$ which are assigned to C_2 and 1,164 with $-\varphi_3$ which are allocated to C_3. Finally, in the fifth step, the final classification is obtained, which is as follows: 1,135, C_1; 2,003, C_2; 2,548, C_3; and 2,471, C_4. The pre-classification of the global search is amended as a result of the two local searches. For example, 142 customers were reallocated from C_2 to C_3 and 59 customers from C_3 to C_2, i.e. the net reallocation between these two groups was 83 customers in favour of C_3. The same is true for the net reallocation of 209 customers from C_2 to C_1 and 339 customers from C_4 to C_3.

In Fig. 2, it can be observed that after applying local searches the algorithm tends to balance the number of customers between the groups. This is due to the reduction of the difference in customers between the most preferred and least preferred of two neighbouring groups. For example, the difference between the least preferred of the first group $-\varphi_2(C_1)$ and the most preferred of the second group $+\varphi_2(C_2)$ is 580 customers (1,079–499 = 580), but after the second local search, this difference was reduced to 162 (870–708 = 162), a reduction of 72 %. A similar pattern is observed between the groups $-C_2$ and $+C_3$, as well as $-C_3$ and $+C_4$ groups, with reductions of 77 % and 71 %, respectively.

Fig. 3 represents the average net flows obtained in the global search for the three criteria dimensions and the segments in the final classification. It is important to note that net flow is defined on the scale [-1, 1], where customers with positive values indicate an overall preference over customers with negative net flows and values close to zero indicate indifference. It can be seen that the figures of the segments are inscribed one inside the other following the order of preference $C_1 \succ C_2 \succ C_3 \succ C_4$ with the exception of the dimension Growth rates, where the groups C_1 and C_2 have on average the same preference. In this analysis, the average net flows indicate a preference for customers in the groups of C_1 and C_2 group, an approximate indifference to the customers of the group C_3 and a lower preference for the group's customers C_4. Details of the average value per criterion can be found in appendix B Table B1.

Statistics have been used to corroborate significant statistical differences between the distributions of each pair of neighbouring groups (C_1-C_2, C_2-C_3 and C_3-C_4) in each of the criteria. In the case of the criteria monetary and variety of products, the values have been transformed to an approximately normal distribution using the Box-Cox method. Subsequently, Fisher's Least Significant Difference (LSD) procedure has been applied at a 95 % confidence level (Moore et al., 2018). The results have shown that there are significant differences between the means of each pair of groups. Therefore, it is guaranteed that for these variables the groups are ordered with means significantly different from each other.

Fig. 4 represents a scatter plot showing the customer net flows after the global search for each of the three criteria dimensions. Customers have been labelled in colours to identify their segment, the distribution of each group and the ascending order between them. Thus, the segment C_4 is in the bottom corner of the graph with the lowest values in all three dimensions, increasing in a diagonal line until reaching the most preferred group of C_1 located in the upper right corner. There is a positive correlation between the RFM and customer collaboration dimensions, confirmed by the Pearson product-moment correlation analysis.

According to the scale of the net flow, in order to make segments more homogeneous, it is desirable that customers in the same group have net flows close to zero and low dispersion. Fig. 5 shows the example of the local searches process for the group C_2 using scatter plots contrasting the customer net flows in the dimensions of RFM and customer collaboration, which represent 80.24 % of the weight of the criteria evaluated. These local searches were applied to the 2,295 customers pre-classified C_2 during the global search. The Fig. 5 (a) shows the result of

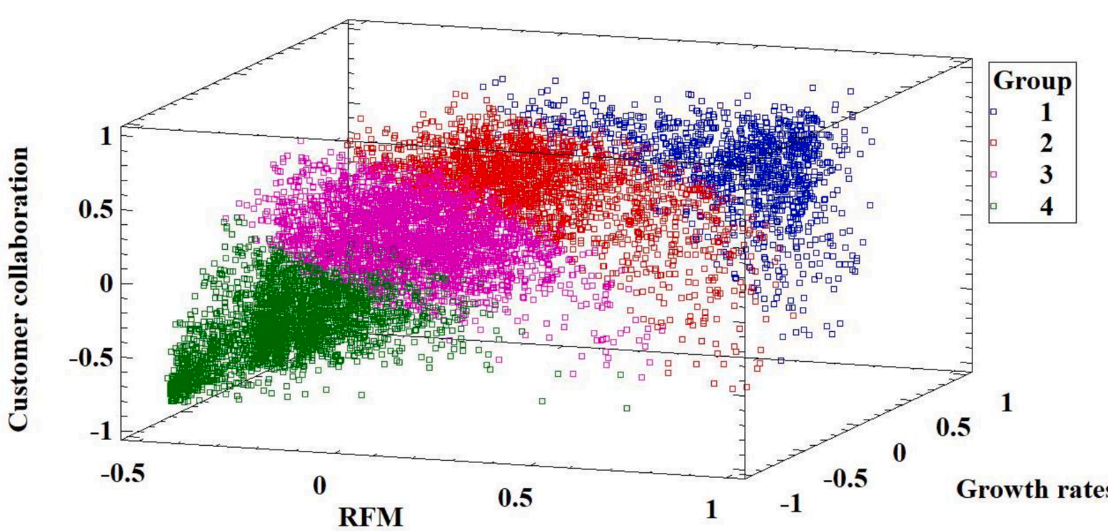

Fig. 4. Scatter plot resulting from the net flow matrix by dimension and segment with the GLNF sorting algorithm.

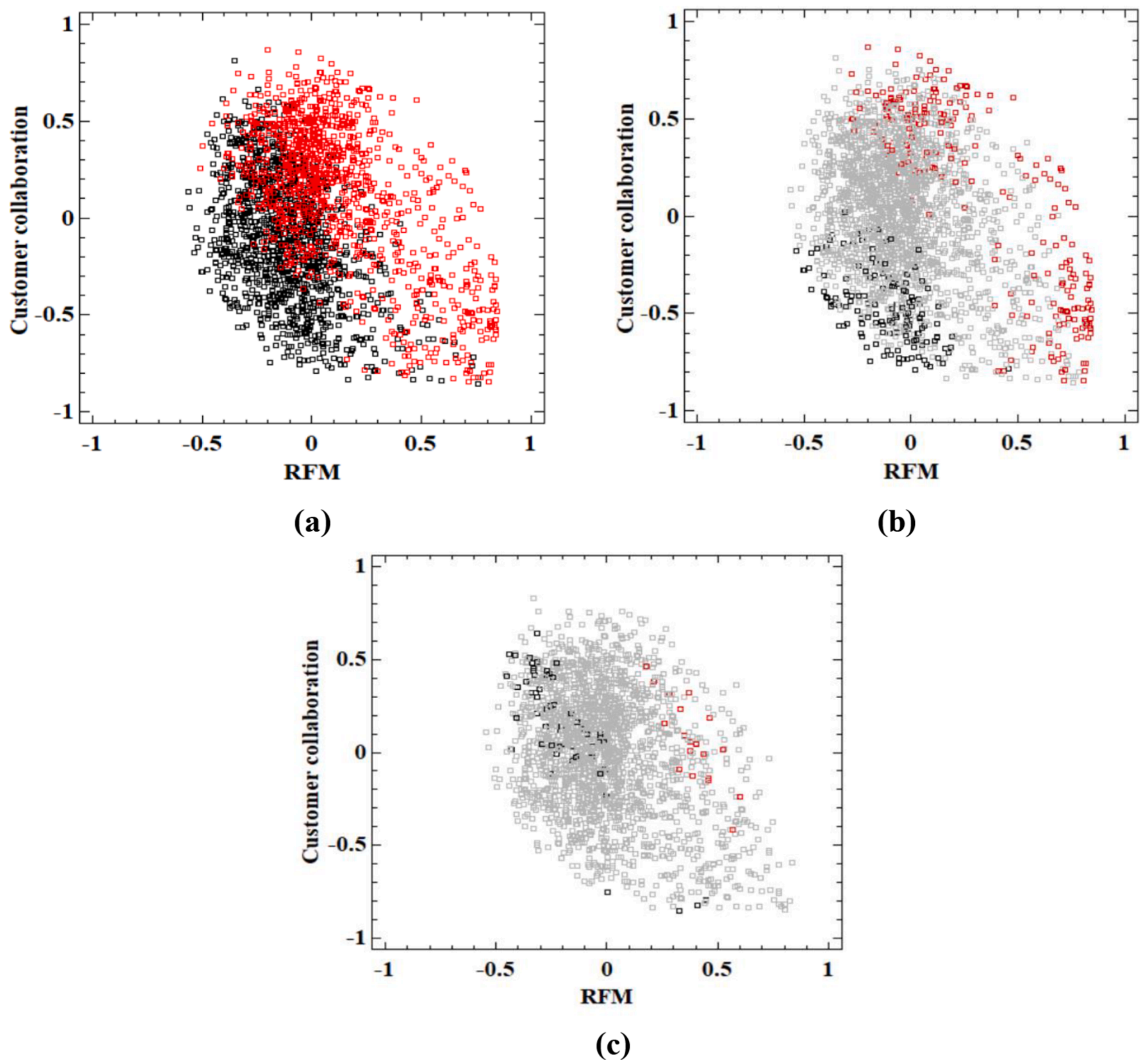

Fig. 5. C_2 customer analysis by RFM vs Customer collaboration. (a) First local search. (b) Second local search. (c) Final classification.

Table 5
Summary of SILS values applied to assignments by GLNF sorting for customer evaluation.

	SILS ($d_t = 100$)			SILS ($d_t = 0.2$)		
	Average ABS	Outside [-1, 1]	Outside [-1.5, 1.5]	Average ABS	Outside [-1, 1]	Outside [-1.5, 1.5]
C_1	0.45	91	17	0.30	0	0
C_2	0.28	68	0	0.23	68	0
C_3	0.24	26	0	0.22	26	0
C_4	0.47	167	44	0.28	0	0
	0.35	352	61	0.25	94	0

the first local search, where 1,216 customers with negative net flow can be observed in black colour $-\varphi_2(C_2)$ and in red 1,079 slightly more dispersed customers with positive net flow $+\varphi_2(C_2)$. Fig. 5 (b) shows the result of the second local search for C_2 where the data in red corresponds to 228 customers with positive net flow $+\varphi_3$ that are reassigned to the top category C_1. In black there are 142 customers with negative net flow $-\varphi_3$ that are reallocated to the lower category C_3. Data in grey correspond to 1,925 customers that are not reallocated and maintain their initial classification. The reallocated customers were far from net zero flow, being located in the top and bottom corner, with high and low preferences respectively for the dimensions considered. In Fig. 5 (c) there are a total of 2,023 customers classified in C_2 where the data in red represents 59 customers who obtained positive flow in the second local search $+\varphi_3$ and who were reallocated from C_3 to C_2 while in black are 19 customers who obtained a negative net flow $-\varphi_3$ and were reallocated from C_1 to C_2. Note that these customers reallocated to C_2 blend seamlessly among the other customers, sharing preference levels. When comparing the dispersions of Fig. 5 (b) and Fig. 5 (c), we observe that the data have become slightly more compact and closer to zero after the second local search. Finally, it can be seen how the proposed criteria allow for the identification of those customers who have a preference with their collaboration and the relationship with the traditional RFM criteria.

5.2. Segmentation analysis with the SILS quality index

Two SILS quality indices have been calculated to represent two scenarios: conservative and flexible. These indices differ in the value of the parameter defining the fictitious dissimilarity with the upper and lower neighbours of the groups C_1 and C_4 respectively. In the conservative scenario it was defined $d_t = 100$ (as in Barrera et al., 2023) with a SILS value that does not favour the reallocation of an alternative to a non-existent segment. In contrast, the flexible scenario defines $d_t = 0.2$ allowing the SILS value to be outside the control limits in favour of a non-existent segment, suggesting the possibility of opening a new group. For example, SILS values of less than -1.5 for a customer classified at C_4

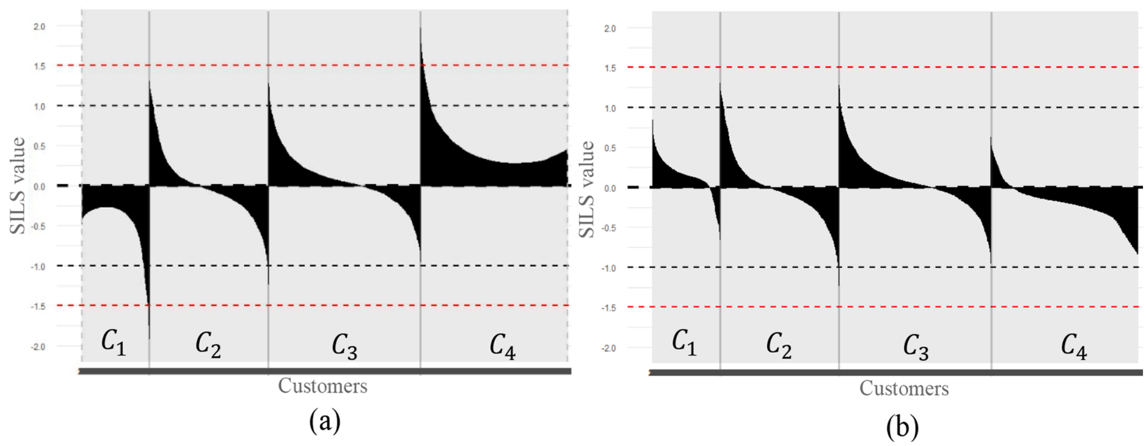

Fig. 6. SILS values applied to assignments by GLNF sorting. Scenarios: (a) SILS ($d_t = 100$). (b) SILS ($d_t = 0.2$).

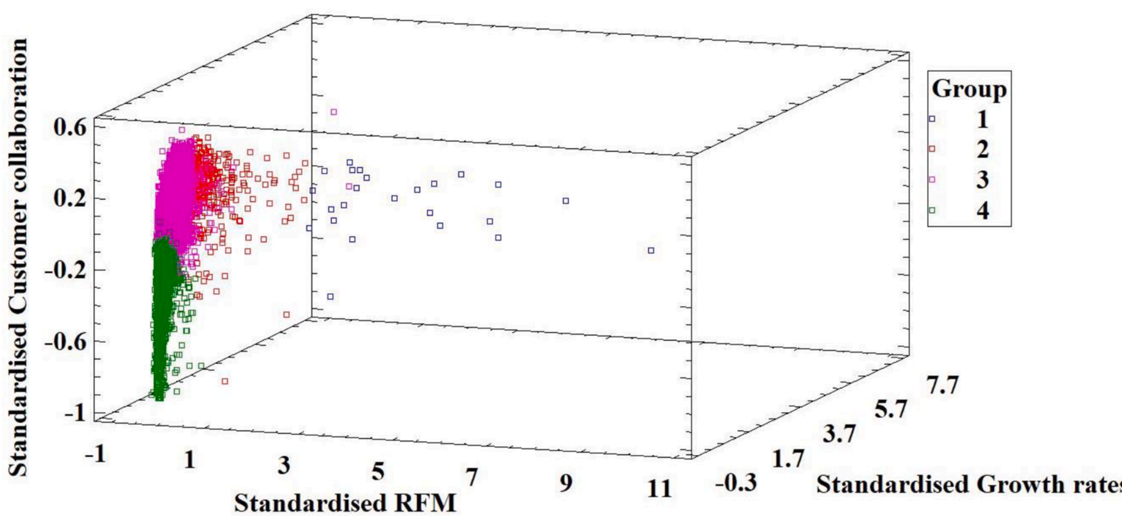

Fig. 7. Scatter plot of the standardised values per dimension with K-means classification.

could indicate the need to consider a scenario with a new group of customers C_5. The calculation of the d_t is based on the fact that five segments perfectly divide the scale of the net flow [-1, 1], with a magnitude of 0.4 corresponding to each. It is divided by five taking into account that there are four real groups and one fictitious group. In this way, theoretically, a customer i classified in C_1 o C_k could be at an absolute distance of up to 0.2 from the centroid of the fictitious neighbouring segments of C_0 and C_{k+1} respectively.

The results after calculating SILS for the two scenarios can be found at Table 5. The average SILS values in absolute value (ABS) for each variation of the parameter d_t are presented. The absolute value has been used because the sign of SILS does not determine the quality of the assignment. Table 5 also indicates the number of customers who obtained SILS values above or below the control limits defined between -1 and 1, and between -1.5 and 1.5. The average values of SILS ABS in both scenarios are relatively low, being lower when $d_t = 0.2$ (0.25). On the other hand, in the conservative scenario, 4.3 % (352) of customers obtained SILS values outside the range between -1 and 1, while in the flexible scenario it was 1.2 % (94). In the latter, no customer obtained SILS values outside the range -1.5 and 1.5. In the conservative scenario, only 61 (0.7 %) customers classified in the groups C_1 and C_4 obtained SILS values outside this range. Therefore, it can be concluded that in both scenarios the number of customers outside the control ranges does not exceed 5 % of the total, which supports the quality of the classifications obtained.

It can also be seen in Table 5 that the differences between the SILS indices obtained with $d_t = 100$ and $d_t = 0.2$ are found in the extreme groups C_1 and C_4 as the change in this parameter only affects these groups. By setting a very large dissimilarity there is an effect on customers in extreme groups close to the border with their neighbouring groups (C_2 and C_3) which can increase or decrease the SILS value and cause the values to go outside the set control limits. In Fig. 6 (a) it can be seen that there are no positive SILS values in C_1 or negative in C_4 but there are some out of control limits at the boundary for these two groups. On the other hand, in Fig. 6 (b) it can be seen that the SILS values of these customers are within the control limits and even positive SILS values in C_1 and negative in C_4. Furthermore, these values are within the control limits, which means that there is no need to consider a new group to improve the classification.

5.3. Segmentation comparison to K-means

The K-means method has been applied to group customers into four categories since according to the literature review it is one of the most used clustering techniques for customer segmentation. The data used are from the evaluation table, the data are standardised by subtracting the mean per criterion and dividing by its standard deviation, and then weighted according to the weight obtained with AHP. The result of the classification was as follows: 24 customers in C_1, 337 in C_2, 5,709 in C_3 and 2,087 in C_4. The segments differ by 45.3 % from those obtained with

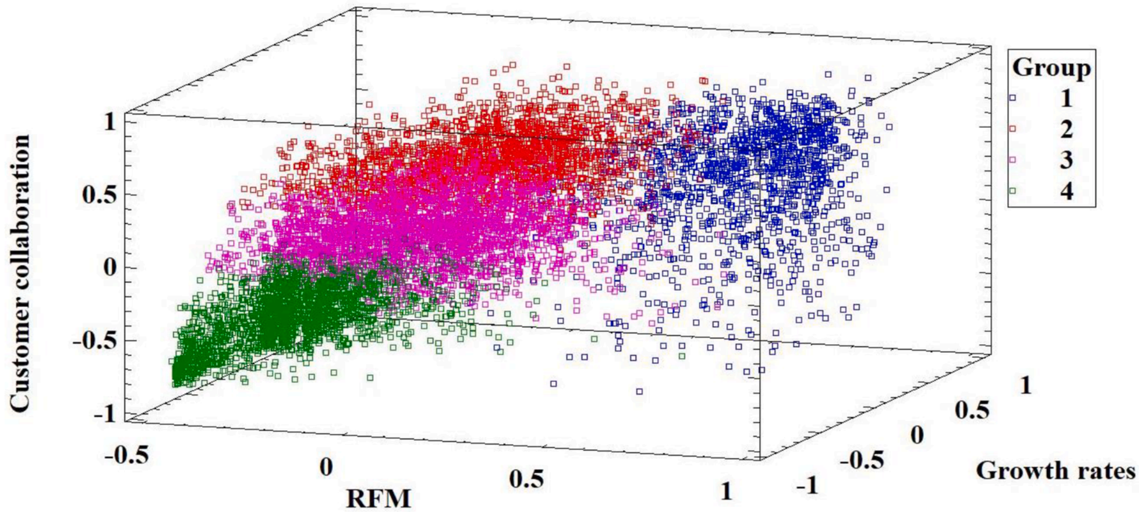

Fig. 8. Scatter plot of net flow matrix by dimension with K-means classification.

Table 6
Contingency matrix between K-means and GLNF sorting.

		GLNF sorting				
		C_1	C_2	C_3	C_4	
K-means	C_1	974	416	34	5	1,429
	C_2	161	1,448	625	4	2,238
	C_3		138	1,876	378	2,392
	C_4		1	13	2,084	2,098
		1,135	2,003	2,548	2,471	8,157

Table 7
SILS results (d_t= 0.2) for K-means.

	Average ABS	Outside [-1, 1]	Outside [-1.5, 1.5]
C_1	0.36	0	0
C_2	0.59	571	119
C_3	0.49	403	73
C_4	0.25	0	0
	0.43	974	192

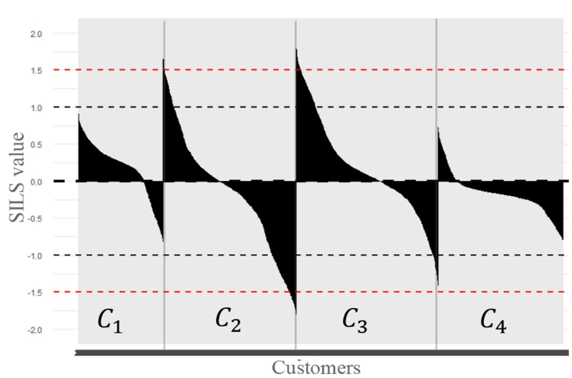

Fig. 9. SILS values (d_t= 0.2) applied to assignments by K-means.

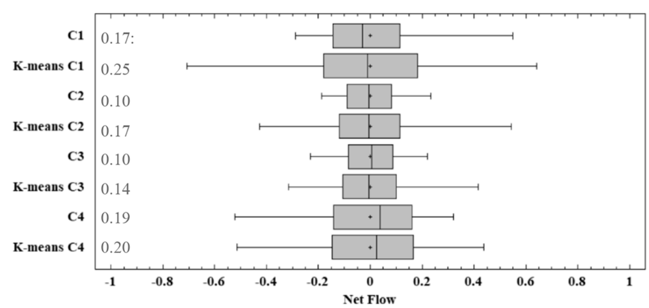

Fig. 10. Box-and-whisker plot of customer net flows grouped with GLNF sorting and K-means.

GLNF sorting. Fig. 7 shows the dispersion for the three criteria dimensions after integrating the nine standardised criteria. In this case it is more difficult to identify an order between the groups, only the DMs' preferences are taken into account in the criteria weights and it is possible that atypical customers may result. Therefore, in order to compare with the proposed model and to include the DMs' preferences, K-means has been directly applied to the net flows matrix resulting from applying PROMETHEE II to the original evaluation table with all customers and limiting profiles. For this comparison with K-means, the initial centroids for the K-means algorithm have been defined using equation (9). The result of the segmentation is as follows: 1,429 customers in C_1, 2,238 in C_2, 2,392 in C_3 and 2,098 in C_4.

Fig. 8 shows the scatter plot of the net flows of the global search for the three dimensions after applying K-means to the net flows matrix. It is observed that the discrimination between customer groups is improved compared to the Fig. 7,the most preferred group of customers can be identified from C_1 and the least preferred group of C_4. However, it is difficult to identify the order of preference between groups and C_2 and C_3 in the RFM dimension, and between C_1 and C_2 for customer collaboration. Appendix B Table B2 gives details of the average values for each criterion by segment.

Table 6 presents the contingency matrix where 6,382 customers (78.2 %) have been classified into the same groups by K-means and GLNF sorting methods. The extreme groups C_1 and C_4 have the largest difference between the number of customers classified for both methods, with 294 and 373 customers respectively.

At Table 7 and Fig. 9 the SILS index results are presented for the classification obtained with K-means, using a $d_t = 0.2$. The results indicate that with K-means, 947 (11.6 %) customers obtained SILS values outside the control limits set at −1 and 1, of which 2.4 % (192) exceeded the control limits of −1.5 and 1.5. In contrast, with GLNF sorting 94 (1.2 %) customers obtained SILS values below and above −1 and 1, and none exceeded the range −1.5 and 1.5. As for the SILS ABS average of each group, it is observed that it is lower in GLNF sorting in

Table 8
Features and comments for each segment.

Group	Description
$C_1$1,135 (13.9 %)	The most preferred customers are those with the best contribution in all three dimensions of criteria assessed. It is essential to maintain strong relationships with these strategic customers, as they are ideal for strengthening and developing new partnership strategies. Cooperation projects that promote a long-term relationship can be carried out, such as sustainability projects, joint product development, effective marketing campaigns for consumers, exclusive supply channels, exclusive discounts, preferential access to new launches, among others. These actions will help maintain their loyalty and maximise their value to the company.Finally, it is suggested to review the amounts set for quota compliance, although these customers showed a good annual growth in monetary terms, there is a decrease between the last two years for quota compliance (GR quota compliance) , which could be due to the erroneous setting of high quota compliance targets.
$C_2$2,003 (24.6 %)	These customers are preferred and loyal to the company and are noted for their good contributions in terms of amount of purchases and variety of brands purchased. While they are already valuable customers for the business, their development can still be enhanced by increasing quota participation and loyalty programmes. In addition, given their strategic importance, they could be considered as partners for the development of collaboration strategies at a lower level than in C_1 but which would further strengthen the relationship between the two parties.
$C_3$2,548 (31.2 %)	These customers have a preference close to zero on the dimensions assessed, which means that their level of attachment to the company is low, but they do not consider themselves disadvantaged. There are opportunities to convert them into preferred customers through strategies that encourage sales and loyalty to the enterprise. To reduce the risk of these customers becoming non-preferred and turning to competitors, collaborative strategies, such as trade marketing, can be developed to communicate the benefits of working with the company to encourage loyalty. In addition, cross-selling can be an option to improve the variety of products purchased by these customers.
$C_4$2,471 (30.1 %)	These customers are the least preferred and have a low level of attachment to the company, resulting in low collaboration and sporadic purchases. However, in some cases, they may represent an opportunity for the business. For example, they could be useful in implementing the clearance sale strategy and reducing inventories. They can also be seen as a test group for launching innovative and risky campaigns or products that might otherwise have a higher risk of rejection by loyal customers. In this way, valuable data could be obtained to improve future campaigns and products and increase their effectiveness in the market.

Note: Below the name of the group, the number of customers is indicated and the percentage it represents of the total number of customers is in brackets.

most groups. The overall average SILS ABS is also lower with GLNF sorting, indicating better quality (Tables 5 and 7).

In order to assess the homogeneity of the groups from another multicriteria perspective, the net flows of the alternatives of each segment generated with GLNF sorting, as well as the alternatives of the segments generated with K-means from the net flows matrix, have been calculated with PROMETHEE. The box-and-whisker plot representing the net flows of the customers is shown in Fig. 10, where the numbers next to the name of each group correspond to its standard deviation. The box represents customers with net flow above the first quartile value and below the third quartile value. Fisher's F-test (Moore et al., 2018) was performed comparing variances between groups obtained with GLNF sorting and K-means, resulting in statistically significant differences at a 95 % confidence interval for the groups C_1, C_2, C_3 and no differences for the C_4 group. A higher dispersion can be observed in the groups obtained with K-means (except for C_4), indicating a lower homogeneity compared to GLNF sorting. For example, the group C_1 found with K-means has a standard deviation of 0.25, a much wider box than the one obtained with GLNF sorting for the same group, as well as whiskers that define a very wide range for the net flows and, therefore, a larger dispersion.

Table A1
Guiding scale for measuring the level of collaboration in reverse logistics and shared information.

Collaboration level	Reverse logistics	Shared information
1 = Very low	The customer shows a lack of cooperation in the process. He or she does not partake in returning or recalling products.	The customer has not shared any relevant information and has shown a lack of willingness to cooperate in the exchange of information.
2 = Lower	The customer demonstrates minimal cooperation. He or she provides limited information and shows resistance to return or recall products.	The customer has shared minimal information, shows no proactivity and has shown significant reluctance to collaborate. Information is only shared when visiting meetings.
3 = Moderate	The customer cooperates in an appropriate manner. He or she provides the necessary information and participates in returning or recalling products in a consistent manner, although occasionally there may be some limitations or delays.	The customer has shared adequate information in most cases, but has occasionally shown limitations in the exchange of information. There is a lack of proactivity, information is shared on request in electronic media and in meetings.
4 = Upper	The customer shows a good disposition. He or she provides relevant information in a timely manner and actively participates in the reverse logistics process.	The customer has shown a willingness to cooperate and has consistently shared relevant information. Information is shared electronically and at regular meetings by agreement.
5 = Very high	The customer is proactive and shows excellent cooperation. He or she provides all necessary information in a timely manner and participates efficiently in the reverse logistics process.	The customer has been extremely collaborative, sharing all necessary information in a timely and complete manner. In addition, an automated interface between the companies' information technology systems has been established, allowing for an efficient and smooth transfer of information.

6. Discussion

6.1. *Customer segmentation by the MRFMC model*

This research has developed a customer segmentation model based on MCDM and a new hierarchy of criteria that integrates RFM and customer collaboration. This model has been validated by classifying 8,157 customers into four ordered groups ($C_1 \succ C_2 \succ C_3 \succ C_4$) according to the company's preferences. The context of application is a B2B model, which is particularly useful when the company as supplier or manufacturer is leading the improvement of the supply chain.

Statistical analyses and the SILS index have been used to evaluate the quality of the ordered segments obtained with the model. According to the results presented in Table 5 and Fig. 6 it is concluded that using a $d_t = 0.2$ is more convenient in this case, since a value of d_t that is too large, such as $d_t = 100$ may generate false positive misallocation alerts for customers who are on the border of extreme groups with their neighbouring groups (C_1-C_2, and C_4-C_3). In addition, the flexible parameter d_t has also allowed the option of opening a new group to be discarded, as there were no SILS values indicating a better assignment in a fictitious group, which has been useful to improve the accuracy of the model. In general, the SILS results and statistical analyses of Fig. 3 and Fig. 4 corroborate the good quality of the segments obtained and the fact that they are ordered.

It is an advantage for the business that the net flows of the RFM and customer collaboration dimensions are positively correlated, as this

Table B1
Average values by criteria applied to assignments by GLNF sorting for customer evaluation.

	Recency	Monetary	Frequency	Quota compliance	Variety of products	Sustainable commitment	GR monetary	GR quota compliance	GR variety of products
C_1	0.10	361.07	11.25	66.55	77.85	3.10	167.41	−9.52	10.91
	(0.38)	(0.71)	(0.60)	(0.55)	(0.58)	(0.04)	(0.31)	(−0.22)	(0.19)
C_2	0.33	83.54	9.78	17.12	74.26	3.00	122.40	−3.00	13.35
	(0.25)	(0.10)	(0.36)	(0.03)	(0.42)	(0.00)	(0.27)	(0.01)	(0.22)
C_3	0.96	37.11	7.41	3.60	66.30	2.98	73.55	−1.44	12.02
	(0.03)	(−0.16)	(−0.01)	(−0.12)	(0.01)	(0.00)	(0.01)	(0.04)	(0.07)
C_4	3.40	13.43	3.32	1.25	44.60	2.93	−4.90	−0.85	−8.49
	(−0.41)	(−0.24)	(−0.56)	(−0.15)	(−0.62)	(−0.02)	(−0.36)	(0.05)	(−0.33)
	1.42	86.42	7.29	14.97	63.29	2.99	74.84	−2.77	5.98

Note: Numbers outside brackets indicate mean values per criterion according to the original assessment matrix. Values in brackets indicate average values per criterion according to the matrix of net flows.

Table B2
Average values by criteria applied to assignments by K-means for customer evaluation.

	Recency	Monetary	Frequency	Quota compliance	Variety of products	Sustainable commitment	GR monetary	GR Quota compliance	GR variety of products
C_1	0.22	334.31	10.78	57.49	74.18	2.98	118.65	−10.75	6.53
	(0.33)	(0.75)	(0.53)	(0.46)	(0.42)	(0.00)	(0.19)	(−0.21)	(0.07)
C_2	0.58	55.90	8.97	13.13	76.22	3.00	93.11	−1.38	11.41
	(0.16)	(−0.06)	(0.24)	(−0.02)	(0.51)	(0.00)	(0.14)	(0.03)	(0.21)
C_3	1.11	32.33	7.31	3.28	63.85	2.99	99.48	−1.31	13.82
	(0.02)	(−0.17)	(−0.01)	(−0.13)	(−0.12)	(0.00)	(0.06)	(0.05)	(0.06)
C_4	3.50	11.79	3.09	1.29	41.43	2.98	−2.59	−0.49	−9.12
	(−0.41)	(−0.25)	(−0.59)	(−0.15)	(−0.70)	(0.00)	(−0.35)	(0.05)	(−0.34)
	1.42	86.42	7.29	14.97	63.29	2.99	74.84	−2.77	5.98

Note: Numbers outside brackets indicate mean values per criterion according to the original assessment matrix. Values in brackets indicate average values per criterion according to the matrix of net flows.

correlation can be used to develop strategies to increase both dimensions at the same time. Table 8 discusses the most relevant characteristics and some suggested strategies to develop each customer segment.

6.2. The MRFMC model and other approaches

In the framework of this research, we have observed the use of the RFM criteria for B2C and B2B models. For the latter, a special approach that considers customer relationships has been proposed to increase the value of the supply chain. Thus, a hierarchy of criteria that extends the traditional RFM model has been designed, incorporating the dimensions of customer collaboration and growth rates. Although the importance of supply chain collaboration has already been addressed in Jadhav et al. (2019), Flynn et al. (2010) and Cao and Zhang (2010), had not been integrated into a hierarchy of criteria that together with RFM customer transactional behaviour was used to segment customers in the B2B model (i.e., Güçdemir & Selim, 2015; Moghaddam et al., 2017; Zong & Xing, 2021). It is also important to note that the weight of customer collaboration is very relevant (31.19 %) according to the experts of the company in the empirical case (see Table 4).

Comparing with the model of Moghaddam et al. (2017), the proposed model assesses product variety more comprehensively on the customer collaboration axis. In addition to the quantity per product, its share in the total quantity purchased is considered. Product variety is also rated according to the company's preferences, taking into account their marketing objective and the ideal proportion of variety they seek to achieve.

Another important contribution of the proposed criteria hierarchy is the inclusion of a criterion to assess commitment to sustainability, including customer commitment to information sharing and reverse logistics. Although it has been previously studied in the literature, such as the work of Van Belle et al. (2021), Zhao et al. (2018) and Khan et al. (2016), we are not aware that it has been included in an evaluation model for customer segmentation.

Unlike models that segment with CTB considering only clustering techniques (Anitha and Patil, 2022; Mahfuza et al., 2022; Stormi et al., 2020), or by integrating them with MCDM techniques to define the importance of criteria or post-classification segments (Bueno et al., 2021; Martinez et al., 2021; Mahdiraji et al., 2019; Güçdemir and Selim, 2015; Liu and Shih, 2005), the proposed system segments customers exclusively using multicriteria techniques, specifically with GLNF sorting that is based on a property of PROMETHEE II net flows. This concept has been shown to have significant discriminant power (Barrera et al., 2022; Rosenfeld & De Smet, 2020; Segura & Maroto, 2017). In addition, another important advantage of the developed decision-making system is that the segments are ordered according to the company's preferences, which facilitates decision-making in the design of marketing strategies.

To compare the customer segmentation obtained with that generated by other approaches, the K-means clustering technique, widely used to solve this problem, has been applied (Anitha and Patil, 2022; Ernawati et al., 2021; Mahfuza et al., 2022; Martinez et al., 2021; Peker et al., 2017; Güçdemir and Selim, 2015). By not considering the DMs' preferences with K-means, it is difficult to identify an order between the groups, as shown in the Fig. 7. However, by applying K-means on the net flow matrix obtained by PROMETHEE, the difference between the two models is reduced. Although discrimination between groups improves in Fig. 8 with respect to Fig. 7, it is not as clear as that obtained with GLNF sorting in Fig. 4. In addition, the comparison of SILS index results in Fig. 6 and Fig. 10 shows that the proposed model performs better in classifying customers into ordered segments based on the DMs' preferences.

In contrast to models based on machine learning, where some techniques can result in black boxes that are difficult to interpret (Doumpos & Zopounidis, 2010; Marcinkevičs & Vogt, 2023), the GLNF Sorting algorithm allows for greater clarity in the analysis of the pre-classifications performed in each of the steps of Fig. 2, which shows the interpretability of the algorithm. Another advantage is the evaluation of the criteria in terms of PROMETHEE preferences, which implies that customer outliers will not significantly affect the results of the segmentation algorithm, unlike what may occur in clustering techniques such as K-means. Conversely, machine learning approach and supervised customer classification methods focus mainly on predictive problems, such as credit default risk, international credit default and supply chain risk, among others (Koç et al., 2023; Kumar and Sharma, 2023; Alp et al., 2011). Furthermore, these techniques have been integrated to improve results, such as the combination of optimisation with Multivariate Adaptive Regression Splines (MARS) (Alp et al., 2011) or clustering (Akteke-Ozturk et al., 2008).

In Casas-Rosal et al. (2023), PROMETHEE II was used to sort customers into categories ordered according to their net flow and that of the limiting profiles, which is equivalent to the global search in GLNF sorting. However, the GLNF sorting algorithm offers a higher discriminative capacity when performing local searches to improve the quality of the clusters, as can be seen in Fig. 5. In this way, greater discrimination is achieved between customers with similar preferences who fall between two adjacent groups.

In FlowSort proposed by Nemery and Lamboray (2008), the net flows of an alternative and the limiting profiles are used to classify one alternative at a time. In contrast, GLNF sorting does not classify individually, it also compares alternatives to discriminate them according to preference values. In segmentation model with a large number of customers, this combination can enrich the discrimination, resulting in an even more robust classification.

This research has also made an important contribution to the validation and extension of the SILS quality index and the GLNF sorting algorithm proposed by Barrera et al. (2023). The effect of the parameter d_t on SILS values, and a modification has been proposed to improve the quality of the indicator in contexts with a large number of alternatives. The GLNF sorting algorithm has been applied in other supply chain contexts when segmenting customers. The scope has been extended in the number of alternatives classified by the GLNF algorithm, classifying 8,157 customers instead of 22 suppliers considered in Barrera et al. (2023). In addition, we also significantly outperformed the number of customers classified with other MCDM models such as those proposed by Casas-Rosal et al. (2023) and Darko and Liang (2022).

7. Conclusions

Customer segmentation plays a key role in customer relationship management (CRM), as it allows companies to increase profitability by implementing strategies tailored to each segment. In this research, a decision support system, called Multicriteria RFM Collaboration, has been proposed to classify customers into groups ordered according to the company's preferences, and without having previously classified customers. The system integrates the multicriteria methods AHP, PROMETHEE II and the GLNF sorting algorithm and extends the traditional RFM criteria-based approach by incorporating the customer's transactional behaviour and collaboration with the customer, including their commitment to sustainability.

This system has been validated through an empirical case involving the segmentation of 8,157 customers in a B2B relationship environment. Four groups of customers have been obtained, ordered according to their preferred characteristics, which allows specific strategies to be suggested for each group. For example, group C_1 was identified as the most valuable and preferred customers for the company, which makes them ideal for joint cooperation projects. On the other hand, group C_4 is composed of customers with a low level of attachment to the company, which can be exploited to implement inventory liquidation strategies.

The proposed system has been compared with an alternative model based on the K-means clustering technique, which is widely used in the literature for customer segmentation. The results indicate that our system is suitable for obtaining segments ordered according to company preferences, making it a viable alternative to traditional data mining techniques.

In short, this research makes significant contributions to the field of MCDM-based customer segmentation models. First, customer collaboration is considered in addition to traditional transactional performance based on RFM criteria, as well as growth rates to take its evolution into account for a complete evaluation of customers. Second, the GLNF sorting algorithm allows discriminating among customers at global and local levels, which are relevant to managers and customers to understand segmentation results and to propose mechanisms for improving relationships in the supply chain management. Third, the GLNF sorting algorithm has been validated to segment thousands of real customers. It could be assumed that it would useful to classify thousands of alternatives in other decision problems. Thus, this contribution represents another important innovation in multicriteria research, where applications have so far considered a limited number of alternatives. Fourth, the SILS index proposed by Barrera et al. (2023) has been extended and improved. An adjustment in the parameterisation of the SILS index has been proposed for use in cases with a large number of classified alternatives. This contribution allows evaluating the quality of customer assignments and indicating the best option of reclassification, in case it is necessary. This detailed analysis of the discrimination capability of GLNF sorting provides the needed transparency, making it a suitable option for real-life scenarios with a large number of customers. In addition, this contribution opens new application areas, such as those related to artificial intelligence approaches, which show an increasing interest to multicriteria techniques.

In summary, the proposed multicriteria model can be the core of a business decision support system with B2B models, enabling a systematic evaluation of customers over time in a targeted marketing segmentation environment. This accurate and orderly segmentation allows companies to maximise targeted marketing strategies and improve CRM in the supply chain.

A possible disadvantage of the proposed system is that it requires some cognitive effort to define the parameters of the preference functions and the number of segments (Ishizaka & Nemery, 2013). However, this effort is compensated by obtaining more organised segments that are better adapted to the specific needs of the company.

Future research may consider extending the model to different industries and sectors by broadening the criteria of the customer collaboration dimension. In addition, it would be interesting to explore the application of the GLNF sorting algorithm and the SILS index in solving problems with a big number of evaluation criteria, such as the evaluation of Environmental, Social and Governance (ESG) performance of companies, a relevant problem in the financial sector worldwide. It would also be interesting to study the sensitivity of the PROMETHEE parameters in big data context, as well as to extend the SILS indicator so that the parameter d_t to be defined depending on the classified data.

Finally, other future line of research is to develop hybrid decision support systems that include multicriteria and data mining modules for unit/alternative classification, which can support users/decision makers to apply the more appropriate approach for a particular decision problem taking into account available data.

CRediT authorship contribution statement

Felipe Barrera: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Marina Segura:** Methodology, Supervision, Writing – review & editing. **Concepción Maroto:** Methodology, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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Appendix A

Table A1

Appendix B

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