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Food market segmentation based on consumer preferences using outranking multicriteria approaches

José Carlos Casas-Rosal[a], Marina Segura[b,*] and Concepción Maroto[c]

[a] Department of Mathematics, Universidad de Córdoba, Avd. San Alberto Magno s/n, Córdoba 14071, Spain
[b] Department of Financial and Actuarial Economics and Statistics, Universidad Complutense de Madrid, Campus de Somosaguas, 28223 Pozuelo de Alarcón, Madrid, Spain
[c] Department of Applied Statistics and Operational Research and Quality, Universitat Politècnica de València, Camino de Vera s/n, Valencia 46022, Spain
E-mail: jcasas@uco.es [Casas-Rosal]; marina.segura@ucm.es [Segura]; cmaroto@eio.upv.es [Maroto]

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Abstract

Market segmentation is a key concept in marketing that groups consumers by their needs, characteristics, or purchasing behavior. The objectives of this research are to develop outranking multicriteria models based on preference ranking organization method for enrichment evaluation (PROMETHEE) in order to segment food consumers and apply them to a survey of healthy and sustainable meat. The models consider two categories of purchasing criteria; one related to product and another to the distributor process. One model generates ordered segments of consumers, while the other obtains four segments according to consumer performance in both criteria categories. An extension of FlowSort method for the sorting problems with Likert scale data is also contributed. The profile of segments shows the significance level of variables such as gender, but mainly those related to food-related lifestyles, when characterizing the consumer groups. This proposal represents a robust approach, which is useful in the effective design of marketing campaigns and policies.

Keywords: market segmentation; sorting problem; classification problem; PROMETHEE; consumer preferences; purchasing criteria; food-related lifestyle; consumer attitudes; healthy meat; cognitive construct

1. Introduction

Sustainable and healthy food consumption is a major concern to many people, which should be supported by society. Nevertheless, this is a very difficult task due to the complex nature of consumer behavior. Marketing analytics provides tools to deal with this issue through the segmentation concept by grouping customers according to a set of criteria (France and Ghose, 2019). The market segmentation problem consists of dividing the market into smaller groups of consumers with

*Corresponding author.

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different needs, characteristics, or behavior. The profile of segments has to be linked to marketing strategies, which can be characterized by socioeconomic and demographic variables, as well as the lifestyle of consumers, among others (Kotler and Armstrong, 2015; Kotler and Keller, 2015).

A good segmentation should minimize differences in needs and wants among customers within segments and maximize the differences among customers from different groups. In the food domain, food-related lifestyle (FRL) is a well-known approach used for market segmentation. In this context, lifestyle is a cognitive construct that includes knowledge of ways of shopping, cooking methods, importance of quality aspects, consumption situations, and purchase motives. This instrument links life values and product-specific cognitions. The idea is to measure how people use food to achieve their life values (Scholderer et al., 2004; Grunert, 2019).

In past decades, market segmentation based on large databases was usually addressed using tools from statistics, data mining, and big data. Nevertheless, segmentation strategies should be focused on consumer behavior to be useful in practice. Psychographic variables, such as people's lifestyles and attitudes, are appropriate for advertising, but they have shown weaknesses in predicting consumer purchasing in any product category. In addition, the multivariate statistical analysis applied in marketing has mainly consisted of clustering algorithms for searching consumer segments and discriminant analysis in order to characterize them. Some authors highlight cluster overlapping (Asgharizadeh et al., 2019) from real data and the difficulty of obtaining compact groups of customers. The lack of robustness and stability of generated clusters (Wang et al., 2008; Van der Zanden et al., 2014; Hajibaba and Grün, 2020), as well as the difficulty managers face in characterizing and understanding them, are common criticisms (Yankelovich and Meer, 2006). Neural networks have similar drawbacks, as the segmentation process is like a black box where the relation between data and results is not transparent and also difficult for marketers to understand (Yang et al., 2012).

Different objectives and products require different data and segmentation strategies in order to identify behavior patterns. Future segmentation approaches should place more emphasis on products, on actual consumer behavior and decision making (Yankelovich and Meer, 2006). While data science mainly contributes with descriptive and predictive analytics, operations research and decision support systems (DSS) provide prescriptive models related to decision making. Literature review highlights the relevance of carrying out interdisciplinary research in coming years in order to advance in real decision making (France and Ghose, 2019).

Multiple criteria decision making (MCDM) provides a powerful approach to deal with the complexity of consumer behavior and many segmentation problems. Nevertheless, to the best of our knowledge MCDM has never been applied to food market segmentation, where it is an appropriate methodology due to the multicriteria nature of consumer decision making, with some rational criteria, some subjective and some emotionally related (Moreno-Jiménez and Vargas, 2018).

The aim of this research is twofold. First, to develop outranking multicriteria models based on preference ranking organization method for enrichment evaluation (PROMETHEE) in order to segment consumers of healthy and sustainable food. Second, to validate these models in a real context by applying them to a consumer survey of healthy and sustainable meat, such as turkey and chicken, both widely consumed foods worldwide.

The main contributions of this research are two models based on a new hierarchy to structure the criteria into two categories, one related to product criteria and another to distributor process. One model generates ordered segments of consumers according to their preferences, while the other obtains four segments according to consumers' performance in both criteria categories. It is interesting to highlight the contribution of an extension of the FlowSort method for the sorting problems whose data are based on a Likert scale, frequently used in marketing surveys. In addition, the profile of consumers in each segment shows the significance level of some variables such as gender, but mainly those related to FRL.

The rest of the paper is organized as follows. After the introduction, the second section presents an overview of the approaches for classification, clustering, and market segmentation. The third section corresponds to the methodological proposal. First, the basic concepts of the PROMETHEE method are summarized, followed by the extension of the FlowSort method for sorting problems to be applied in marketing studies. Then, the design of the hierarchy of customers' purchasing criteria and the survey to elicit preferences and other consumer data are explained. Finally, the third section also includes the methodology applied to characterize the consumer profile in each segment. The fourth section presents the results obtained from both outranking approaches. The discussion section compares the results of both techniques and highlights their advantages compared to other tools, such as multivariate statistical analysis and neural networks. Conclusions and future research are outlined in the final section.

2. Market segmentation approaches: clustering, classification, and sorting

There are a huge number of market segmentation methods that can be classified into two groups: *a priori* and *post hoc* segmentation. The former is based on prior knowledge related to consumers or products, such as demographic features and purchasing amount. The *post hoc* segmentation is based on market data-driven analysis. The variables selected to segment the market can be general (lifestyles, demographics, etc.) and product-specific, for instance consumer's preferences, demands, and buying behavior (Han et al., 2014).

The main idea behind market segmentation is to group customers into homogeneous sets, which are then profiled according to some variables. For both, segmenting and profiling customers, there are a huge number of variables or criteria to be used. On the one hand, a literature review showed that variables used for segmentation and profiling are related to personality characteristics, FRLs, and behavior (Verain et al., 2012). On the other hand, Van der Zanden et al. (2014) consider two main categories, characteristics-based and preference-based. The former segments consumers into groups with similar characteristics, useful for communication and targeting. In the latter, based on preferences, the consumers have similar needs and wants, which are useful for product development and strategy.

Cluster analysis is one traditional multivariate statistical technique used for customer segmentation in marketing that includes a wide range of grouping techniques, with the *k*-means algorithm being used frequently (Guçdemir and Selim, 2015; Hajibaba and Grün, 2020). In particular, the literature provides applications in the food domain, such as Drichoutis et al. (2007), Verain et al. (2012), Van der Zanden et al. (2014), and Oeser et al. (2019). In customer relationship management, classification and clustering are useful for customer identification, as well as for attraction, retention, and development of customers (Ngai et al., 2009). In addition, data mining also provides other technologies for clustering, such as fuzzy sets and neural networks (Hiziroglu, 2014; Griva et al., 2018; France and Ghose, 2019), as well as big data (Verdenhofs and Tambovceva, 2019).

Cluster analysis has an exploratory nature and has been applied to descriptive market segmentation for one or more than one set of variables, but in both cases, there is only one objective to optimize in order to measure the segment homogeneity. In predictive market segmentation, it is important to optimize the homogeneity of segments, as well as their prediction ability. Market segmentation is a multiple criteria problem, in which both profiles and responses of consumers have to be similar (Liu et al., 2012). In the literature, there are evaluations of clustering algorithms based on MCDM techniques that show that no single method provides the best performance on all measures (Barak and Mokfi, 2019). Van der Zanden et al. (2014) also highlight that there is no single right approach to segmenting consumers and markets.

One weakness of clustering methods is the lack of information on the importance of customer segments generated, which is essential in marketing decisions. Research also overcomes this drawback by combining traditional clustering algorithms, for instance k-means, with other multicriteria approaches such as the fuzzy analytic hierarchy process (AHP) to determine the importance of clusters (Guçdemir and Selim, 2015). Some recent research papers have integrated multicriteria concepts such as outranking flows of alternatives into objective functions from unsupervised clustering algorithms (Bai et al., 2019). In addition, the literature also provides sorting methods that apply concepts from clustering (De Smet et al., 2012; Costa et al., 2020).

Marketing surveys frequently apply the Likert scale, as in Serrato et al. (2010) and Oeser et al. (2019), widely used in opinion studies for their simplicity. Nevertheless, a difficulty in marketing studies is the handling of Likert-scale data (Arunachalam and Kumar, 2018), which generate ordinal qualitative variables for which the application of traditional statistical techniques is not suitable. Moreover, there are some weaknesses related to suitable results for decision making, definition of dependent variables and exclusion of important factors. According to several authors, MCDM provides alternative tools to statistical approaches (Zopounidis and Doumpos, 2002; De Smet et al., 2012; Liu et al., 2012).

MCDM has been applied in marketing because consumers evaluate products according to several criteria. In particular, Multi-Attribute Utility Theory (MAUT) has mainly been used to model consumer purchasing behavior and disaggregation methods to analyze customer preferences. Multiple criteria outranking methods have not yet been applied to solve marketing problems, which is an area of future research, as some authors have highlighted (Tsafarakis et al., 2010).

MCDM provides a relevant methodology and tools to deal with complex problems, such as classification, sorting, and ranking, in order to find robust solutions for decision making (Zare et al., 2016; Lai and Ishizaka, 2020). Zopounidis and Doumpos (2002) reviewed the literature focused on multicriteria classification and sorting methods, which both assign all alternatives, items or actions to predefined groups. In the former case, the groups are defined nominally, while in sorting methods the groups are ordered, from the segment with the most preferred alternatives to those with the least preferred. Some reference profiles define and distinguish the groups in both methods, which have many real applications, including marketing.

The contribution of MCDM to segmentation literature is shown in the large number of research articles on multicriteria classification problems, which deal with the assignment of a set of alternatives into predefined classes or categories (Doumpos and Zopounidis, 2018). Disaggregation methods represent a theoretical approach to build models of the multicriteria classification using data-driven methodology from small data sets. The models consider value functions or outranking relations between alternatives. Multicriteria models are easier for decision makers to interpret and understand than those from data mining/statistical learning theory, focused on their predictability based on large and complex data sets (Doumpos and Zopounidis, 2011).

In solving real problems, until now MCDM has been more widely applied in other fields, such as finance (Grigoroudis et al., 2002; Zopounidis and Doumpos, 2002; Zhang et al., 2009) and supply chain management, than in marketing. In the supply chain, MCDM models have been developed for supplier segmentation with great success in order to identify the best relationship between companies and providers. For instance, Araz and Ozkarahan (2007) solved the problem by a sorting method based on PROMETHEE, while Segura and Maroto (2017) and Segura et al. (2019) used PROMETHEE to classify suppliers and (Rezaei et al., 2015) applied the multicriteria approach known as the best worst method. Thus, an important contribution to consumer segmentation using a multicriteria approach can also be expected.

The multicriteria literature provides several techniques for solving classification and sorting problems, which could be useful in market segmentation. Multicriteria classification methods, which group alternatives into predefined and non-ordered categories, are focused on theoretical aspects without real-world application to validate them (Costa et al., 2020). Those proposed by Nemery and Lamboray (2008) or De Smet et al. (2012) highlight for sorting problems, where the groups are ordered. The latter classified the units based on the definition of the inconsistency matrix, which allows grouping to be performed while minimizing inconsistency between groups. Sarrazin et al. (2018) proposed measures based on PROMETHEE I that help to interpret and better understand the quality of the partition obtained. The sorting problem can also be resolved through PROMETHEE II, based on the concept of the net flow of all units, dividing the set ordered into the desired number of groups. Boujelben (2017) defines the concepts of preference profile of a cluster and similarity and inconsistency profiles of a cluster. He applies them to an example of supplier segmentation.

Finally, the previous analysis from the literature review of clustering, classification, and sorting methods shows several shortcomings of the traditional clustering methods in market segmentation, which can be overcome by appropriate multicriteria models for classifying and sorting customers. Outranking methods based on PROMETHEE have been successfully applied for previous steps in sustainable food supply chains, such as supplier segmentation.

3. Methodology

This research proposes to carry out market segmentation according to consumer purchasing criteria elicited using the Likert scale and two outranking multicriteria approaches based on PROMETHEE. The decision criteria are structured into categories through a hierarchy, which allows grouping of consumers by solving multicriteria classification and sorting problems.

Thus, the first step in this proposal consists of identifying the main decision criteria and developing the hierarchy that groups the criteria into relevant categories related to customer behavior and/or needs with respect to the type of product. The second step is to elicit the customer preferences using a survey asking the importance of buying criteria, as well as information to characterize the consumers, such as socioeconomic, demographic, or lifestyle data, among other variables. The third step is to segment consumers using one of the outranking approaches presented in this section and analyze the results through visualization capabilities of these methods. Finally, the consumers

Table 1
Evaluation table

Alternatives	Indicators and weights of evaluation criteria					
	g_1 w_1	g_2 w_2	... ...	g_j w_j	... ...	g_q w_q
a_1	$g_1(a_1)$	$g_2(a_1)$	...	$g_j(a_1)$	...	$g_q(a_1)$
a_2	$g_1(a_2)$	$g_2(a_2)$	...	$g_j(a_2)$	...	$g_q(a_2)$
...	...	...	...	...	...	...
a_i	$g_1(a_i)$	$g_2(a_i)$	...	$g_j(a_i)$	...	$g_q(a_i)$
...	...	...	...	...	...	...
a_n	$g_1(a_n)$	$g_2(a_n)$	...	$g_j(a_n)$	...	$g_q(a_n)$

in each segment should be characterized according to relevant variables to better identify the target customers and improve decision making.

This section first presents the PROMETHEE method for classifying customers, followed by the extended FlowSort based on PROMETHEE used to deal with Likert data and obtain ordered segments. Then, the multicriteria model is shown in the hierarchy with the criteria categories designed for market segmentation of healthy meat. Finally, the survey carried out and the techniques to characterize the segments are explained.

3.1. The PROMETHEE method

PROMETHEE is an outranking method developed by Brans in 1982, which allows the solving of many multiple criteria problems with a finite number of alternatives for choice, ranking, and classification/sorting purposes.

Let $A = \{a_1, a_2, \ldots, a_n\}$ is a set of alternatives (actions, units, consumers, customers, suppliers, etc.) to be evaluated using a set of criteria $\{g_1, g_2, \ldots g_q\}$. Table 1 shows the evaluation table with the basic data, which are the quantitative or qualitative indicators to measure the performance of each alternative for each criterion. PROMETHEE also requires additional information on the preferences between criteria. This is provided by the weights $w_1, w_2, \ldots w_q$ that represent the relative importance of the evaluation criteria (Table 1).

PROMETHEE is based on pairwise comparison between alternatives. The preference for alternative a compared to b, $P(a, b)$, is based on the difference between the values of criteria in both alternatives, as follows:

$$P_j(a, b) = F_j\left[d_j(a, b)\right] \quad \text{for all alternatives in A,}$$

$$\text{where} \quad d_j(a, b) = g_j(a) - g_j(b) \quad \text{and} \quad 0 \le P_j(a, b) \le 1.$$

The larger the difference between criterion values, the greater is the preference for the alternative that performs better. These preferences are represented by real numbers between 0 and 1.

There are six types of function to express the preferences within the criteria. Thresholds of indifference and strict preference are used in some functions to consider negligible differences, as well as others sufficient for full preference.

A basic concept of PROMETHEE is the aggregated preference indices for each pair of alternatives a and b, which are defined as follows:

$$\pi(a,b) = \sum_{j=1}^{q} P_j(a,b)w_j \quad \pi(b,a) = \sum_{j=1}^{q} P_j(b,a)w_j,$$

where $\pi(a,b)$ is the sum of all preference values multiplied by the weights. It expresses the degree to which alternative a is preferred over b. Thus, $\pi(b,a)$ is the degree to which the alternative b is preferred over a. From aggregated preference indices, the positive outranking flow, negative outranking flow, and net outranking flow of each alternative are calculated as follows:

$$\varphi^{+}(a) = \frac{1}{n-1}\sum_{x\in A}\pi(a,x) \quad \varphi^{-}(a) = \frac{1}{n-1}\sum_{x\in A}\pi(x,a)$$

and

$$\varphi(a) = \varphi^{+}(a) - \varphi^{-}(a).$$

The positive outranking flow represents the strength of the alternative, in other words, to what extent an alternative outranks all the others. The higher the positive outranking flow, the better is the alternative. The negative outranking flow of an alternative means to what extent an alternative is overcome by the others. The lower the negative outranking flow, the better is the alternative. These concepts allow a partial ranking of alternatives, while the net flow generates a complete ranking. A detailed explanation of PROMETHEE is available in Brans and De Smet (2016).

3.2. PROMETHEE for sorting problems: extended FlowSort

PROMETHEE allows the definition of classification-nominal groups. To generate sorting-ordinal groups based on this method, it is necessary to extend PROMETHEE, as Nemery and Lamboray (2008) did in the extension developed, known as FlowSort. In the following section, an extension of FlowSort is proposed for cases in which the evaluation table data are based on a Likert scale, as frequently applied to marketing surveys.

3.2.1. The sorting problem

Let

$$a_1,\ a_2,\ \ldots,\ a_n$$

be a set of n customers of a particular product or service whose market you want to segment. The customer purchase criteria are grouped into the following categories:

$$CC_1,\ CC_2,\ \ldots,\ CC_p.$$

For each category i, a set of criteria is defined:

$$g_1^j,\ g_2^j,\ \ldots,\ g_{q_i}^j,$$

so that g_j^i denotes criterion j of the category i with $i = 1, 2,\ \ldots,\ p$ and $j = 1,\ 2, \ldots,\ q_i$. The customer valuation for each of these criteria will be measured through a Likert-type scale of m_i values.

The objective is market segmentation by sorting-ordinal groups. Thus, given the categories CC_i, it defines the ordered groups

$$C_1^i \succ\ C_2^i \succ \cdots \succ\ C_{k_i}^i,$$

in such a way that $C_r^i \succ\ C_s^i$, with $r < s$, indicates that the customer is included in group C_r^i show a higher degree of preference for the criteria category CC_i than those included in C_s^i.

The problem posed is one of classification, in the sense that the number of groups, K_i, defined for each criteria category CC_i is imposed *ad hoc*. Problems in which the number of groups is not imposed *a priori* are known as clustering problems.

The simplest sorting problem would be that in which the customers were divided into two groups for each category of criteria, in such a way that one would include customers with a high degree of preference in the category criteria, while those with the lowest degree of preference would be included in the other group.

3.2.2. The extended FlowSort method

Next, the FlowSort developed by Nemery and Lamboray (2008) is extended to the case of customer segmentation based on preferences shown in responses from a set of criteria for the purchase of the product or service using a Likert-type scale.

For each criteria category CC_i with $i = 1,\ 2,\ \ldots,\ p$, we define k_i ordered groups

$$C_1^i \succ\ C_2^i \succ \cdots \succ\ C_{k_i}^i,$$

in such a way that a customer's inclusion in one of these groups will depend on the degree of preference for the criteria category CC_i, so that those customers with a greater degree of overall preference in the criteria of this category will be included in the C_1^i group. The degree of preference is measured on the basis of the customer valuation of different criteria

$$g_1^j, g_2^j, \ldots, g_{q_i}^j,$$

from a Likert-type scale with values $1,\ 2,\ \ldots,\ m_i$. To facilitate the comparison of preferences between the different criteria of the same category, equality and the number of criteria within a category will be imposed as a condition. However, as will be seen below, the method developed does not require the imposition of this condition.

To calculate the degree of preference, and depending on the number k_i of groups that we want to create, an ordered partition of the Likert scale is performed:

$$R^i = \left\{ r_1^i = 1, r_2^i, \dots, r_{k_i+1}^i = m_i \right\},$$

which will define the previously established groups, in such a way that C_j^i will be determined by the limits r_j^i and r_{j+1}^i. The linearity assumed for a Likert variable makes it advisable (although not necessary) that the values of the R^i should be equidistant, in such a way that between two consecutive values, the numerical distance is

$$d^i = \frac{m_i - 1}{k^i}.$$

On the other hand, it uses v_{jk}^i to designate the response given by the customer j $(j = 1, \ 2, \dots, \ n)$ to criterion k $(k = 1, \ 2, \dots, \ q_i)$ from category i $(i = 1, \ 2, \dots, \ p)$. From this, for each customer and category, we construct q_i sets, formed by the union of R^i and evaluation of v_{jk}^i for each of the criteria $g_1^i, g_2^i, \dots, g_{q_i}^i$. In other words, for each category i, each customer j and each criterion k, we construct the set

$$R_{jk}^i = \left\{ r_1^i = 1, r_2^i, \dots, r_{k_i+1}^i = m_i, \ v_{jk}^i \right\},$$

with v_{jk}^i bounded between 1 and m_i.

Thus, for each category CC_i we have alternative $k_i + 2$ with values for criteria q_i. PROMETHEE is then applied to the set of alternatives thus defined, as explained in Section 3.1. From this application, for each customer j and each category CC_i, it will obtain a set of net flows $k_i + 2$:

$$\varphi_{r_1}^i, \varphi_{r_2}^i, \dots, \varphi_{r_{k_i+1}}^i, \ \varphi_{v_j}^i,$$

where $\varphi_{v_j}^i$ *is* the net flow of customer j for the category i.

It is evident that v_{jk}^i for any criterion k ensures that $\varphi_{v_j}^i$ verifies that

$$min\left(\varphi_{r_1}^i, \varphi_{r_2}^i, \dots, \varphi_{r_{k_i+1}}^i\right) \leq \ \varphi_{v_j}^i \ \leq \ max\left(\varphi_{r_1}^i, \varphi_{r_2}^i, \dots, \varphi_{r_{k_i+1}}^i\right).$$

Moreover, the net flow value of the customer for this category will be comprised between the net flows of the two consecutive values of R^i, which classifies the customer into one of the groups defined in the ordered set $C_1^i \succ \ C_2^i \succ \cdots \succ \ C_{k_i}^i$.

Therefore, the assignment criterion will be as follows:

A customer a_j is included in the set C_s^i if and only if their net flow $\varphi_{v_j}^i$ verifies that

$$\varphi_{r_s}^i \leq \varphi_{v_j}^i < \varphi_{r_{s+1}}^i.$$

Following the application of this procedure $n \cdot p$ times, we will have the assignment of the n customers for the p categories of criteria analyzed.

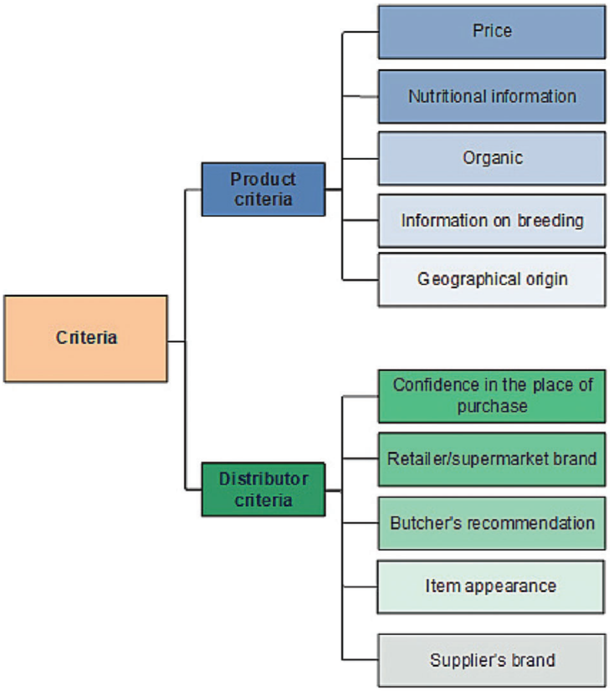

Fig. 1. Hierarchy of purchasing criteria of customers when buying healthy meat.

3.3. Hierarchy of purchasing criteria and consumer survey

This research proposes a market segmentation based on the importance attributed by consumers to purchasing criteria for turkey and chicken meat (both fresh and prepared). Ten criteria grouped into two categories are considered. One category is related to product-associated criteria and another category includes the criteria corresponding to the distribution process, as shown in Fig. 1. The importance is measured by a Likert scale from 1, not at all important to 5, very important. Thus, all values on the evaluation table are from 1 to 5. This scale is frequently used in marketing studies and recommended for telephone surveys (Serrato et al., 2010; Escriba-Perez et al., 2017; Oeser et al., 2019).

The classification and sorting methods based on PROMETHEE and the extended FlowSort for Likert-scale data are applied and validated using data from a survey carried out in Spain in May and June 2018. The consumer sample, randomly selected, consists of 625 telephone interviews with an error of ±4.0% at a confidence level of 95.5% in Spain and an equal allocation among the different geographical areas of mainland Spain. The duration of interviews was 12 minutes approximately and they were held using a computer-assisted telephone interview system. The interviewees are people aged between 18 and 75 responsible for food purchasing or sharing this responsibility in households where chicken and turkey meat is consumed (Baviera-Puig et al., 2021).

The survey includes 64 questions, arranged into six groups, as follows: interviewee selection, shopping habits and purchasing criteria, consumption habits, image, food lifestyles, and identification data. The questionnaire is available as Appendix.

From the data survey, the criteria have an importance, which range from 8% to 12%. For multicriteria segmentation, the weights of all criteria are 10%. Therefore, the weight of product criteria is 50% and the same value is for distributor criteria. The preference function used to apply PROMETHEE is linear with a threshold of strict preference of 4 (maximum difference between values, five minus one). The objective is to maximize all criteria.

D-Sight software was used to apply PROMETHEE to classify consumers according to their net flows for product and distributor criteria. Implementation in R software was required to segment consumers according to the extended FlowSort method.

3.4. Customer characterization

Once the customer classification for each of the criteria categories has been assigned individually, the customers in each group can be characterized in a unifactorial or multifactorial design. In unifactorial characterization, for each category i, we have a sample of customers classified into k_i groups ordered by one of the previously cited methods. On the other hand, multifactor characterization proposes a classification based on two or more categories of criteria, based on the previous unifactorial classification.

For example, if the customers are classified on the basis of two criteria categories CC_i and CC_j with k_i and k_j groups, respectively, the cross-combination of both will define a partial order classification in the $k_i \; x \; k_j$ groups.

The simplest multifactorial classification is that consisting of two categories that classify each one into only two groups: customers with a high degree of preference for that criteria category, and those with a low degree of preference. The crossing of groups classifies customers into four groups: those with a high degree of preference for the two criteria categories, those with a low degree of preference for both, and another two groups in which we find customers with a high degree of preference in one of the categories and low in the other. While the first two groups contain customers with clear behavior, the last two groups include customers who show different behaviors between the different criteria categories used to segment the market for the product or service.

After defining the interest groups for the person in charge of the study, the customers can be characterized by comparing the groups with respect to the background variables. To this end, it is possible to opt for the application of inferential techniques such as Chi-square independence comparisons, comparison distribution tests such as Mann–Whitney or Kruskal–Wallis, or mean comparison methods are such as t-tests, depending on the nature of the variables used.

The results of the different tests will allow customer characterization according to the background variables, with the important feature that the clients are grouped according to the degrees of preference for the different criteria categories used to rate the product or service.

4. Results

4.1. Customer segments and profile obtained by PROMETHEE

PROMETHEE is applied to the evaluation table where purchasing criteria for turkey/chicken meat are those in the hierarchy of Fig. 1, grouped in two categories: product-related criteria and

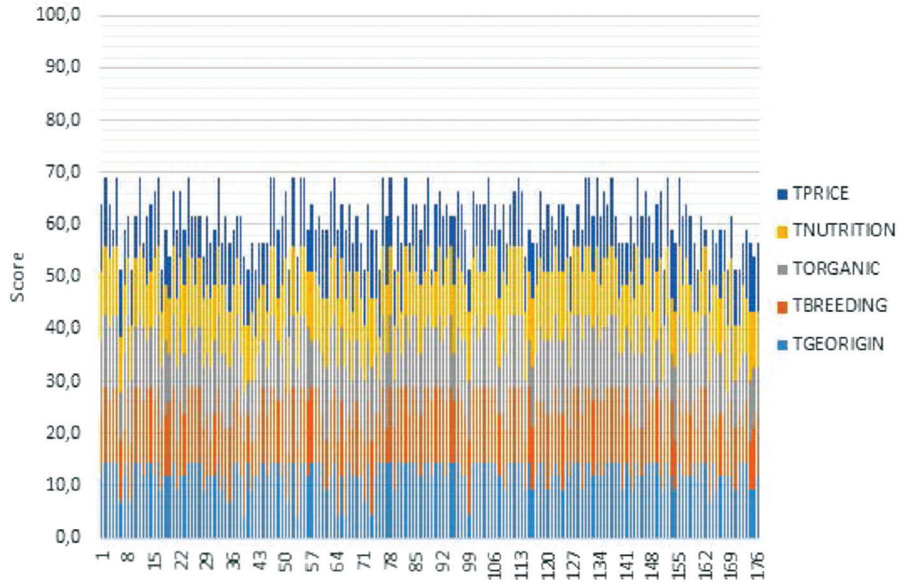

Fig. 2. Contribution of product criteria for customers with high scores in the product and distributor criteria: turkey meat.

distributor-related criteria. Each consumer is an alternative to classify in one of the four segments, which can be generated from the net flow scores for product criteria and distributor criteria, as shown in Table 2. There are 474 valid answers for turkey and 548 for chicken from the survey carried out in 2018.

The net flows of consumers obtained by PROMETHEE are between -1 and $+1$. D-Sight software used for the analysis changes these values to scores from 0 to 100, which are easier to understand for decision makers. Thus, four segments are defined. S1 includes customers whose scores in product and distributor criteria are above 50 (High). If the score in a group of criteria is lower than 50, it is labeled "Low" in Table 2. Establishing four segments according to the high or low performance of alternatives has been used in other segmentation studies (Grigoroudis et al., 2002; Valadares-Tavares, 2003; Segura and Maroto, 2017).

Table 2 highlights the two more important segments, which are S1 and S4, with 37% and 31% of the interviewees for turkey. These data are similar for chicken, 38% and 31%, respectively. S1 gives high importance to both product and distributor criteria, whereas the relevance of both groups of criteria is low in S4. If the profile of these consumers is characterized clearly, marketers can design polices focused on 68–69% of the market. S2 and S3 have scores high in one group of criteria and low in another. They represent a lesser market percentage than S1 and S2.

Figures 2 and 3 show the contribution of product and distributor criteria for turkey consumers with high scores in both of them. There are no significant differences among average ages of the consumers classified in the four groups.

Table 2 also presents the profile of turkey and chicken consumers in the four segments generated. In particular, the characteristics and questions that reflect the lifestyles in which there are 99%

Table 2
Customer segments of turkey and chicken meat based on PROMETHEE method

	PROMETHEE		
Segment	Product score	Distributor score	Profile: Significance level 1–5% in turkey (T), chicken (C), or both (B)
S1	High	High	(B) Gender: greater percentage of women than men
			(T) Number of people who live the household
Turkey 37%			(B) Lower educational qualifications
			(B) More people choose traditional store for fresh turkey/chicken
Chicken 38%			(T) More people choose traditional store for prepared turkey/chicken products
			(B) They like to read the food product labels and know their composition
			(B) Advertising helps them decide which foods to buy
			(B) They like doing their household food shopping
			(B) I like shopping in specialist stores where they can advise me
			(B) They keep an eye on the changes in price of the foods they usually buy
			(B) They prefer to buy natural products, e.g., preservative-free products
			(T) They always try to get the best quality at the best price in foods
			(B) They like to try new foods
			(B) They like buying organic products if they have the chance
			(B) They think it is more important to choose food products for the nutritional value rather than their flavor
			(B) They like to spend a lot of time cooking
			(B) They like cooking and experimenting with new recipes
			(B) At home, they normally use ready-to-eat foods, such as salads
			(B) The family gets involved in preparing meals
			(B) The woman is responsible for achieving a healthy and nutritional diet for the family
			(B) They find cooking very satisfying
			(B) They only buy and eat products that are familiar to them
S2	High	Low	(T) Number of people who live the household
			(C) They like to read the food product labels and know their composition
Turkey 15%			(B) They prefer to buy natural products, e.g., preservative-free products
			(B) They like to try new foods
Chicken 19%			(B) They like buying organic products if they have the chance
			(B) They think it is more important to choose food products for the nutritional value rather than their flavor
			(B) They like to spend a lot of time cooking
			(B) They like cooking and experimenting with new recipes
			(B) The family gets involved in preparing meals
			(B) They find cooking very satisfying
S3	Low	High	(C) More people choose traditional store for fresh chicken
Turkey 17%			(T) Higher purchasing frequency of prepared turkey products
Chicken 12%			(T) Advertising helps them decide which foods to buy
			(C) They only buy and eat products that are familiar to them
S4	Low	Low	(C) Gender: greater percentage of men than women
Turkey 31%			(C) Higher purchasing frequency of prepared chicken products
Chicken 31%			(C) They like less doing their household food shopping
			(C) They like less shopping in specialist stores where they can advise me

Continued

Table 2
Continued

Segment	PROMETHEE		Profile: Significance level 1–5% in turkey (T), chicken (C), or both (B)
	Product score	Distributor score	
			(C) They keep an eye on the changes in price of the foods they usually buy (C) They always try to get the best quality at the best price in foods, but less than other groups (T) Number of people who live the household (T) Lower purchasing frequency of prepared turkey products (T) People prefer packaged products (T) They only buy and eat products that are familiar to them

Note. 474 consumers in turkey and 548 in chicken.

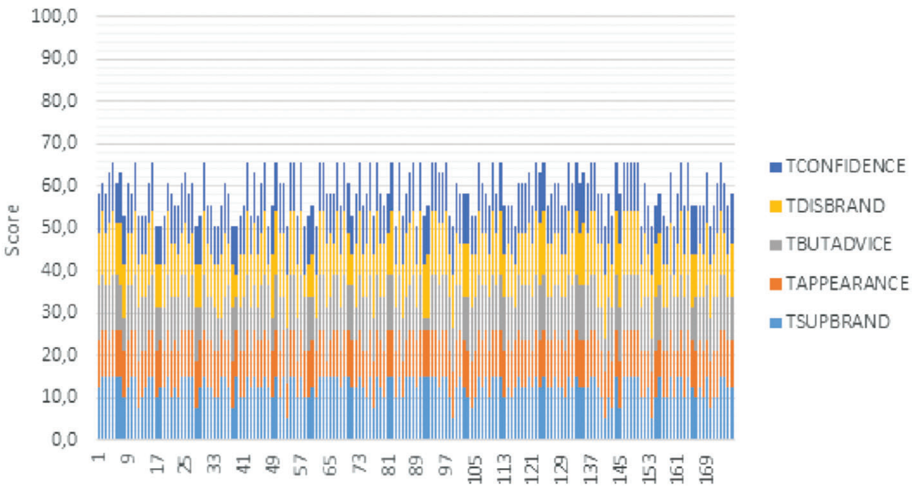

Fig. 3. Contribution of distributor criteria for customer with high score in product and distributor: turkey meat.

significant differences between the segments in most cases are included, some being significant at 95% and 90%. Some relevant outcomes of the study are highlighted below.

The gender division is significant, as more women present high scores for both product and distributor than men. Specifically, three of four consumers in this segment are women, as shown in Fig. 4 for turkey.

Approximately, two of every three consumers with high scores in product and distribution have a lower level of education (primary and secondary) than those in other segments in which higher studies have greater representation (50%). The customers with high scores in both criteria tend to shop more in traditional stores, whereas large supermarket chains are chosen more by consumers with high scores in either product or distribution. In terms of format, the consumers who prefer packaged product are those in the low scoring segment (54% in turkey and 40% in chicken).

As for the questions that reflect the lifestyles of consumers, and in particular their purchasing behavior, some 80–84% of those who present high scores in product or both (product and distribution)

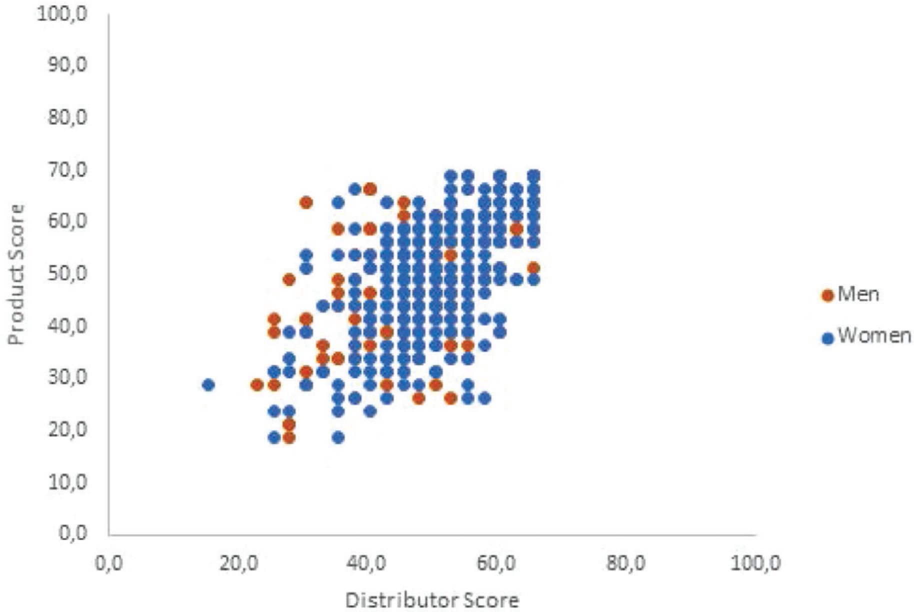

Fig. 4. Distribution of customers by distributor and product scores and gender. Significant differences in the Fisher test: turkey meat.

like to read the label and know the product composition. Also in the S1 segment, the percentage of consumers (20%) who say that advertising helps them decide what to buy is higher.

Between 82% and 80% of turkey and chicken buyers in S1 like to go household food shopping, while this percentage is 67% and 60%, respectively, in S4. There are also important differences regarding shopping in specialist stores that advise the consumer. Whereas in S1 these consumers are 74% and 75%, in S4 they represent 36% and 40%, for turkey and chicken, respectively. In S1, 40% of the sample are highly focused on prices, while this percentage falls to 17% in the S4 segment.

Regarding qualitative aspects, turkey and chicken consumers have very similar behaviors. Specifically, 78% in S1 and S2 prefer to buy natural products, while this percentage is between 44% and 50% in segments S3 and S4. As for obtaining the best quality at the best price (value for money), 70% in S1 and one of two in the other segments agree more with this statement. Half of consumers with both high scores like to try new foods, although this proportion drops to 29% in segments with low product and distribution scores.

Regarding the willingness to buy organic products, the differences are important between segments S1 and S2 with S3 and S4. Both in turkey and chicken, 50% of consumers with high scores in product and distribution or high in product alone are favorable, whereas this behavior reaches 11–18% in S3 and S4. Slightly less than half of S1, both in turkey and chicken, consider the nutritional value of food more important than flavor, with a small proportion of consumers in the other segments following this behavior.

In terms of the relationship with the way food is prepared, approximately 28% of S1 like to spend a lot of time cooking, this percentage being between 10% and 18% in the other segments, both for turkey and chicken consumers.

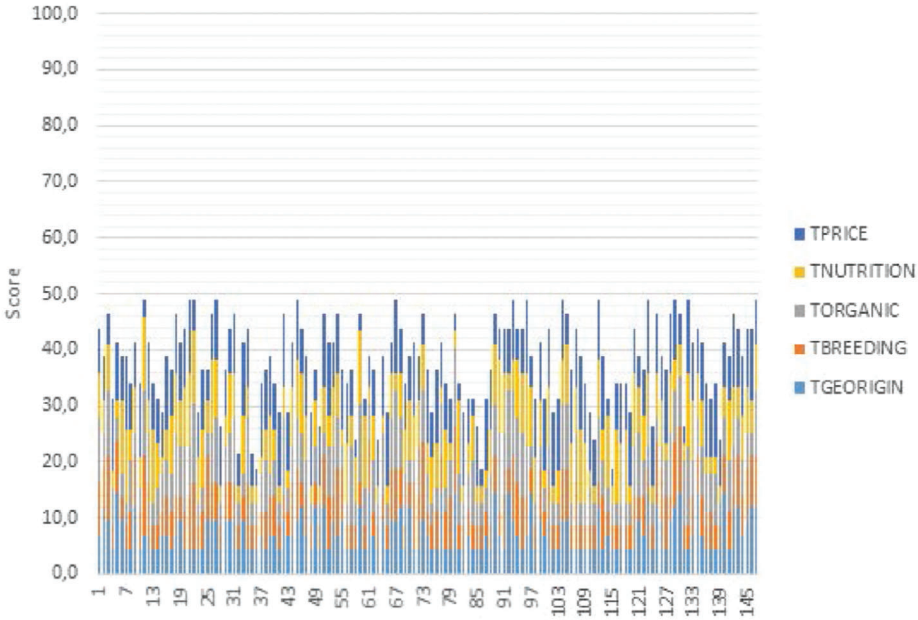

Fig. 5. Contribution of product criteria for customers with low scores in the product and distributor criteria: turkey meat.

In S1 and S2 for turkey, between 42% and 48% of consumers like to experiment with new recipes, while in S3 and S4 this proportion is 25%. The behavior is similar in chicken consumers. Slightly less than one third of the consumers with high scores use ready-to-eat foods (salads), whereas in the other segments this percentage is halved.

Families are more involved in preparing meals in segments with high scores in product and in both. One of two interviewees in S1 consider that the female head of the household is responsible for a healthy and nutritive diet.

Finally, in terms of motivations for choosing food, for 40% of consumers with high scores in product and distribution cooking is very rewarding, while this percentage in the low scoring segment is 19%, with similar data in turkey and chicken. In terms of buying only foods that are familiar to the consumer, one of every three consumers in S1 and S3 and fewer in S2 and S4 agree with this statement (18%).

In the segment of consumers who value the product criteria much more than those of the distributor (S2), most of the significant variables and questions that reflect their lifestyles are also significant for S1 consumers and likewise present similar behavior in the two types of meat.

Figures 5 and 6 show the contribution of product and distributor criteria for turkey consumers with low scores in both categories of criteria. In this case, as well as the groups with one score high and the other low, the differences between men and women are not significant for turkey meat. The main reason for consumption of turkey meat is that it is healthy, being the percentage of customers between 35 and 37 in all groups. In chicken, these percentages range between 30 and 37.

Segment S3, in which the consumers rated the distributor criteria more than the product criteria, presents differences between turkey and chicken consumers. The same can be said of the consumers

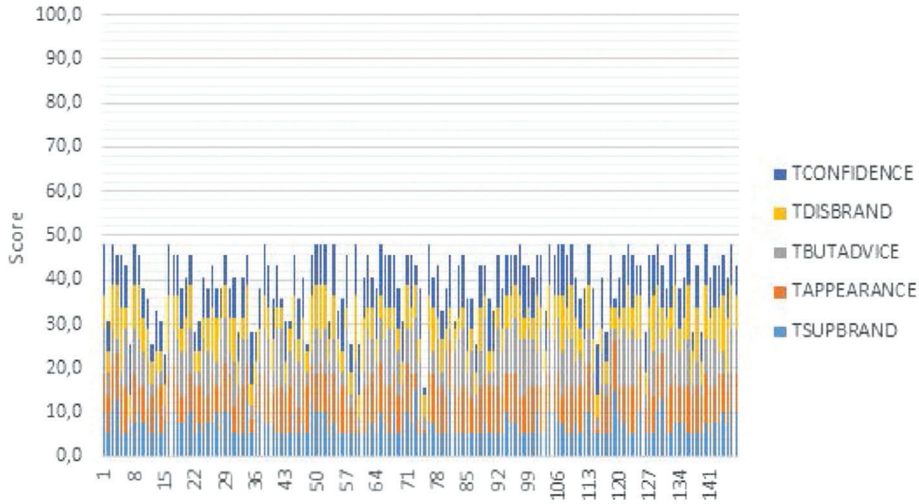

Fig. 6. Contribution of distributor criteria for customers with low scores in the product and distributor criteria: turkey meat.

in S4, who place little value in either product or distributor criteria. Thus, in S4 the highest percentage of men in this segment is significant in the purchase of chicken, but not turkey.

4.2. Segments and profile of customers obtained by extended FlowSort method

This section presents the segmentation of consumers that was achieved by applying the extended FlowSort sorting method. Table 3 shows the size of the consumer groups and their profile through the significant differences observed in their behavior. Segment S1, with high scores for product and distribution, groups 60% and 64% of turkey and chicken consumers, respectively. In this group, three of every four consumers are women, both in turkey and chicken. The proportion between men and women is more balanced in the other segments.

In the first segment with high scores for product and distribution, there is a greater number of large families. In contrast, in S4, with low scores for both criteria, there is greater representation of single-person or childless families.

Consumers with a lower level of education are more represented in S1 than in the other segments, both for turkey and chicken. Both types of meat also share that three of four consumers like to read the product label, as well as a greater proportion of people for whom advertising guides their purchasing decisions and preference for natural products, among others, as can be seen in Table 3.

More than half of the turkey and chicken consumers with high scores in product and distribution like shopping in specialist outlets. These consumers and those with high distribution scores are the ones who are most attentive to price changes.

Some 70% of the people in S1 prefer natural products, and this percentage is higher (80%) for those with a high score in the product criterion. These differences are 99% significant with other segments. These groups of consumers are also those who try new foods, buying organic products and for their nutritional value (40–60%).

Table 3
Customer segments of turkey and chicken meat based on extended FlowSort method

Segment	Extended FlowSort Product score	Extended FlowSort Distributor score	Profile: significance level 1–5% in turkey (T), chicken (C) or both (B)
S1	High	High	(B) Gender: greater percentage of women than men
			(T) Number of people who live the household
Turkey 60%			(B) Lower educational qualifications
			(C) Higher purchasing frequency of fresh chicken
Chicken 64%			(B) They like to read the food product labels and know their composition
			(B) Advertising helps them decide which foods to buy
			(B) They like shopping in specialist stores where they can advise them
			(B) They keep an eye on the changes in price of the foods they usually buy
			(B) They prefer to buy natural products, e.g., preservative-free products
			(T) They always try to get the best quality at the best price in foods
			(B) They like to try new foods
			(B) They like buying organic products if they have the chance
			(B) They think it is more important to choose food products for the nutritional value rather than their flavor
			(B) They like to spend a lot of time cooking
			(B) They like cooking and experimenting with new recipes
			(B) The family gets involved in preparing meals
			(T) They find cooking very satisfying
			(C) They only buy and eat products that are familiar to them
S2	High	Low	(T) Gender: greater percentage of men than women
			(T) Number of people who live the household
Turkey 6%			(C) Higher purchasing frequency of fresh chicken
			(B) They like to read the food product labels and know their composition
Chicken 5%			(B) They prefer to buy natural products, e.g., preservative-free products
			(B) They like to try new foods
			(B) They like buying organic products if they have the chance
			(T) They think it is more important to choose food products for the nutritional value rather than their flavor
			(T) They like to spend a lot of time cooking
			(T) They like cooking and experimenting with new recipes
			(B) The family gets involved in preparing meals
			(T) They find cooking very satisfying
S3	Low	High	(T) Educational qualifications
			(T) Advertising helps them decide which foods to buy
Turkey 21%			(C) They keep an eye on the changes in price of the foods they usually buy
Chicken 20%			(C) They only buy and eat products that are familiar to them
S4	Low	Low	(B) Gender: greater percentage of men than women
			(T) Number of people who live the household
Turkey 13%			(T) They don't like doing their household food shopping
			(B) They like less shopping in specialist stores

Continued

Table 3
Continued

Segment	Extended FlowSort		Profile: significance level 1–5% in turkey (T), chicken (C) or both (B)
	Product score	Distributor score	
Chicken 11%			(C) Fewer people choose traditional store for fresh and prepared chicken/more people choose local supermarkets and big chain supermarkets for fresh chicken/they prefer packaged format for fresh chicken/they like less doing their household food shopping/they prefer to buy natural products, lesser than other groups/they always try to get the best quality at the best price in foods, but lesser than other groups/they do not like to spend a lot of time cooking/they do not like cooking and experimenting with new recipes/they do not find cooking very satisfying

Note. 474 consumers in turkey and 548 in chicken.

The segments are also distinguished by the way foods are prepared. Between 42% and 44% of people in S1 and S2 like to experiment with new recipes, while this percentage is halved in consumers with low scores (S4). A similar behavior pattern to this is observed in terms of the family being involved in meal preparation.

In S1, more than 40% of the interviewees responded that the woman of the household is responsible for providing a healthy and nutritious diet. In segments S1 and S2, the proportion of respondents for whom cooking is very rewarding is greater. Roughly one third of interviewees in S1 and S3 only buy food that is familiar to them, this being a higher percentage than in the rest of the groups.

Table 3 also shows that the behavior of turkey and chicken consumers is more homogeneous in the segment of high product and distribution scores than in the other three. Thus, many variables that reflect the lifestyles of consumers are significant for turkey consumption, but not in the case of chicken.

4.3. Sensitivity analysis and group stability

The weights of criteria considered to obtain the consumer groups by PROMETHEE and extended FlowSort methods, explained in two previous subsections, are equal to 10% for all of them. Sensitivity analysis provides information on the stability of the consumer groups generated by these multicriteria approaches. As a classification problem, it is interesting to know whether the majority of consumers continue to belong to the same group when the importance of the criteria used to solve the problem changes. If so, the groups are stable. Considering survey data, the classification problem has been also solved for a scenario with the following weights in order to represent possible changes in practice. For product criteria (50%), the importance of criteria is price (5%), nutritional information (15%), organic (10%), information on breeding (5%), and geographical origin (15%). For distributor criteria, the weights are confidence in the place of purchase (15%), retailer/supermarket brand (5%), butcher's recommendation (5%), item appearance (10%), and supplier's brand (15%).

The percentage of common consumers in both scenarios for chicken is 95% in the most important segment, S1, obtained by PROMETHEE. This number is 92% for S4, 84% and 94% for S2 and S3, respectively. Data for turkey are slightly lower, with 88% of consumers that match in both scenarios for S1 and S4. The sensitivity analysis for the extended FlowSort method provides a higher level of stability of the first group, S1, which varies between 96% and 97% for turkey and chicken, respectively, being lower than the percentage of common consumers in the other three segments (70–92%). Therefore, the multicriteria approaches proposed for consumer segmentation generate robust groups, as shown in the cited results.

5. Discussion

5.1. Market segmentation by outranking classification and sorting methods

Analyzing in detail the results presented in the previous section, the interviewees' preferences show the same profile of turkey and chicken consumers both for those with high assessment in product and distribution and those scoring high for product only, S1 and S2, when classifying consumers by PROMETHEE method (Table 2). This behavior pattern can be explained by the similar market positioning of both types of meat as healthy food. No reasons for consumption of turkey and chicken, both fresh and prepared, showed significant differences between the segments. Nevertheless, the figures highlight healthiness as the most relevant characteristic in both types of meat for one third of interviewees. Taste is ranked in the second place with 21% in turkey and 30% in chicken, while good price and quality are only important aspects for 9% of interviewees in turkey and 12–15% in chicken. The remaining motives for consumption, such as if the children like it, being easy to make or part of the diet, are only highlighted by a smaller percentage of people.

Although fresh turkey and chicken purchasing habits presented no significant differences between segments, it is interesting to highlight that 99.6% of interviewees buy fresh chicken. In 92%, the frequency is once a week, every two weeks, or more often. In contrast, these figures drop to 42% for prepared chicken products such as burgers and sausages. The same data are quite different for turkey products, where prepared meat is as popular among consumers as the fresh product. From our survey, approximately 50% of people purchase fresh and prepared turkey at least once a week or every two weeks.

The consumption figures are similar to those for purchasing; on average, 55% of people consume fresh turkey at least once a week and the percentage is similar for prepared product. In contrast, 89% of people eat fresh chicken once a week or more often, compared to only 54% for prepared product of this meat. These results are similar to those from previous studies for chicken consumption, while turkey purchasing and consumption have increased in recent years (Escriba-Perez et al., 2017).

If we compare the profile of consumers in the segments obtained by classifying and sorting methods based on PROMETHEE, the S1 segment has the same sociodemographic variables, as well as food lifestyles, which are significant for turkey. In contrast, there are only small differences in the consumer behavior related to chicken alone. In both approaches for turkey and chicken meat, there is a higher percentage of women than men in the S1 segment. Consumers with lower educational qualifications also have greater percentage in this group compared to others.

In the S1 segments of Tables 2 and 3, the customer preferences in responses to lifestyle questions show similar attitudes in shopping behavior (the importance of information of product labels, advertising, price, etc.), the qualitative aspects of meat (natural/organic products) and in the interest in and ways of cooking.

In Tables 2 and 3, a different profile of turkey and chicken consumers is observed in segment S4, where the consumers have low scores for product- and distributor-related criteria. In the group generated by PROMETHEE some variables, such as gender, are significant for chicken, but not for turkey. In the group S4 obtained by extended FlowSort method, there are more men than women in relation to both types of meat. Nevertheless, many lifestyles-related responses are significant for chicken, but not for turkey, as can be seen in Table 3.

Comparing the quantity of consumers within the segments, two of three consumers are assigned to segments S1 (37% in turkey and 38% in chicken) and S4 (31% in both products) by the PROMETHEE method. In FlowSort approach, these data account for 60–64% of consumers in S1 and a small number in S4, with 13% and 11% for turkey and chicken, respectively. This difference can be explained by the allocation mechanism in both approaches. In PROMETHEE, the pair comparisons between consumers take all interviewees into account. The extended FlowSort method considers pair comparisons between the reference profiles and one consumer at a time.

Summarizing, the consumer profiles of the S1 segment from PROMETHEE and S1 from Extended FlowSort are quite similar for both chicken and turkey, as well as from both multicriteria segmentation methods. The greater percentage of women than men is highlighted in both meats and methods. The same occurs in other related socioeconomic variables, such as lower educational qualifications and the number of people who live the household. Moreover, most of the FRL variables are also significant for consumers in both S1 segments and meats. In short, food product labels, advertising, price, nutritional value, natural and organic products are important to them. In addition, they like cooking and find it very satisfying, which is a reason for choosing food.

The consumer profile of S1 from PROMETHEE and Extended FlowSort has important practical implications for marketing in agribusiness and food distribution companies, as well as governments in developing new products and strategies to promote healthy and sustainable lifestyle. The S2 segment from PROMETHEE also shares some significant FRL variables with S1. In total, S1 and S2 represent 57% of chicken consumers and 52% in the case of turkey. The representation of S1 from Extended FlowSort is 64% and 60% for chicken and turkey, respectively. Thus, the multicriteria sorting method allows bigger segments, which have sufficient entity to be targeted for marketing strategies and administration campaigns.

In contrast, S4 segments with low scores in product and distributor are smaller from the sorting method than from PROMETHEE. The latter groups 31% for both meats, while the sorting method classifies 13% for turkey and 11% in chicken in this segment. The profile of these consumers is quite different for chicken and turkey, but they share a significantly greater percentage of men than women for chicken and prefer package format.

5.2. *Multicriteria outranking methods and other approaches*

This work is part of a multidisciplinary research project in which the consumers' segmentation was also carried out using a cluster analysis approach. The FRL were the segmentation variables, instead of profiling variables as in the multicriteria approach explained before. In particular, factor analysis was used to decrease the number of variables related to FRL from 23 to 7 factors. Then, cluster analysis was applied to estimate the number of segments using Euclidean squared distance to measure the similarity among consumers and the Ward method to obtain clusters (Baviera-Puig et al., 2021).

From the same survey and real data, the following five groups of consumers were identified by cluster analysis: manager cook (24.5%), healthy cook (20.8%), concerned with cooking, but not cooks (22%), total detachment (11.9%), rational shopper with little interest in cuisine (20.8%). On the one hand, it can be highlighted that all the purchasing criteria for turkey and chicken are significant when they are used to profile clusters. The main differences appear from consumers in the group of total detachment with respect to the rest. On the other hand, when profiling the four multicriteria segments using FRL variables, many of these are significant.

In particular, the food lifestyles that characterize the two segments of manager cook and healthy cook, such as interest in cooking, interest in quality, and healthy and organic products are all significant in S1 segments from PROMETHEE and Extended FlowSort methods. Similarly, clustering and multicriteria segments have shown similar performance related to the gender variable. There is a greater percentage of men than women in S4 (low preference for product and distributor criteria) and the total detachment segment. These last two groups are equivalent to those identified by other authors as careless or uninvolved segments (Verain et al., 2012).

When comparing the results from the multicriteria approach to those from cluster analysis in Baviera-Puig et al. (2021), the size of segments should be highlighted, being bigger in multicriteria methods. This represents an advantage for the latter in order to establish strategies and campaigns to promote the consumption of healthy and organic food. In addition, it is also relevant to point out that multicriteria segmentation is easier to understand by managers and administrations in contrast to other methods from data science, as other authors have stated previously.

The customer categories obtained by clustering tools are the result of the assignment procedure, while they are previously defined when multicriteria techniques for classification and sorting problems are applied. This is an important difference between these two approaches. In addition, segments from cluster analysis can overlap (Asgharizadeh et al., 2019) and lack stability (Van der Zanden et al., 2014; Hajibaba and Grün, 2020). In the literature, the number of segments in the food domain range from four to five, with one or two careless or uninvolved segments (Verain et al., 2012), which can be compared to S4 groups in the multicriteria approach of this research.

Multicriteria analysis based on the PROMETHEE method provides scores which, presented by criteria categories with visualization tools, are very useful to understand the results and to inform decision making, as can be seen in this research and other real applications (Behzadian et al., 2010; Nemery et al., 2012; Segura and Maroto, 2017; Segura et al., 2019). In contrast, marketers consider multivariate analysis and neural networks, among other data science tools, as a black box used to obtain clusters that are difficult to interpret and with weak prediction capacity (Doumpos and Zopounidis, 2010; Tsafarakis et al., 2011). In particular, the cluster analyses based on the FRL approach, used for decades in marketing studies, establish 23 dimensions in 5 domains that have been a barrier to its application (Grunert, 2019).

In general, multicriteria approaches are associated with small number of alternatives to be classified, as in Valadares-Tavares (2003), whereas tools from data mining or big data can deal with large databases. Nevertheless, there are some real applications based on PROMETHEE, which involve several thousand alternatives (Gallego et al., 2019). In addition, the use of hierarchies in multicriteria approaches helps to structure problems and give valuable insights which are very useful for decision making (Belton and Stewart, 2002).

Van der Zanden et al. (2014) distinguish two groups of approaches for segmentation: characteristics-based and preference-based. The latter classifies consumers according to similar wants and needs, which contributes insights useful for product development and strategy. This research proposes eliciting the customer preferences through the Likert scale and the weights of criteria from a survey. This approach is easier to carry out than pairwise comparison in some experiments for disaggregation methods, which then apply MAUT to derive preference functions.

6. Conclusions

This research provides new models and insights for solving a relevance problem: market segmentation using an outranking multicriteria approach. These models have been applied to healthy meat, fresh and prepared chicken and turkey, two of the most important and affordable sources of protein for people worldwide. This research extends the FlowSort method for the sorting problems and applies it to consumer segmentation in the healthy food sector, where the data-driven approach uses Likert scale based surveys to determine the consumer preferences. This research is also the first market segmentation proposal based on purchasing criteria, which groups them into two categories: product and distributor.

The ordered segments obtained by the extended FlowSort method are compared to segments generated from net flows of PROMETHEE for categories of criteria, which allow us to pinpoint the consumer preferences. Both methodologies provide good market segmentation, as they clearly profile consumers whom the criteria of products and distribution have high preference and those whose assessment is low. Visualization of the results of the outranking analysis, such as the contribution of criteria to consumer preferences, provides insights from a new perspective that is a strength of this proposal for food consumer segmentation. These models can form the core of DSS for companies and public organizations in order to develop new prepared meats and campaigns to encourage a healthy and sustainable lifestyle.

This research shows that the multicriteria segmentation proposal represents a new perspective for dealing with food segmentation problems and generates bigger segments than those from cluster analysis, the insights being compatible and consistent in both methodologies. This is an advantage of the MCDM approach, which requires good knowledge about relevant criteria to elicit the consumer preferences. Segmentation based on cluster analysis needs appropriate metrics to solve a specific problem, as no one method is the best for all types of problems (Everitt et al., 2011; Barak and Mokfi, 2019).

Multicriteria models generate robust consumer segments, whose number is defined according to the net flow concept, while this number is unknown in the cluster analysis approach. Thus, multicriteria models are easier to implement in DSS than those based on data mining techniques. Both multicriteria approaches represent a promising new perspective to determine consumer preferences in the food sector. They also provide complementary results to those obtained from multivariate analyses where segmentation variables are based on the FRLs. With both, as an alternative and as a complementary methodology, marketers have tools for customer identification, design strategies for attraction, retention, and development of customers and the marketing mix design (product, place, price, and promotion) for healthy food.

Sustainable food segmentation distinguishes several categories of variables, such as personal (need for cognition, values, etc.) and lifestyle (organic beliefs, environmental concern, healthy lifestyle, etc.) (Verain et al., 2012). They can be used as consumer segmentation variables or as consumer profiling variables. Although this research adds purchasing criteria, there is a limitation related to the lack of emotions considered in the analysis. Future research should enrich the analysis with emotion-related variables in order to derive knowledge from attitude and motivation purchasing and their relation to consumer preferences. Some authors have shown that emotions can predict consumer behavior better than traditional cognitive measures (White and Yu, 2005).

Consumers' decisions are the result of subjective factors that can be captured by multicriteria techniques, which always include some subjectivity through preferences of the decision maker. It would be interesting to enlarge the number of criteria to elicit consumer preferences and design other categories to group them. Validation of this multicriteria approach to market segmentation for other food and products from other sectors are future lines of research, which require investigation regarding the most suitable criteria for the type of products and customers. Synergies between the neuromarketing field and multicriteria classification and sorting methods can provide advances in market segmentation in future. This would allow improvements in decision making related to designing marketing campaigns and policies effectively.

Finally, the sorting outranking method proposed will be applied and validated in the previous phase of the food supply chain for segmentation of suppliers according to sustainability criteria, as well as consumer needs. Chai and Ngai (2020) highlight and recommend the application of sorting methods as one gap in this latter field that should be overcome in future research.

Acknowledgments

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Appendix: Analysis of turkey and chicken consumption

Group 1: Selecting the interviewee

1. Are you one of the people in your household that participates in food purchasing?
2. Age
3. Gender

Group 2: purchasing habits

1. Can you tell me how often you buy fresh turkey meat to consume at home?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
2. Can you tell me how often you buy prepared turkey products (burgers, sausages, sliced, marinated, etc.)? To consume at home?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
3. Can you tell me how often you buy fresh chicken meat to consume at home?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
4. Can you tell me how often you buy prepared chicken products (burgers, sausages, sliced, marinated, etc.)? To consume at home?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
5. Thinking only about fresh turkey meat, do you usually shop for it at…?
(1—traditional store (local butcher/delicatessen/shop); 2—local supermarket; 3—indoor and outdoor markets; 4—street markets; 5—big chain supermarkets (Mercadona, Consum, Caprabo, etc.); 6—large-scale hypermarkets (carrefour, Alcampo, etc.); 7—others)
6. Thinking only about fresh chicken meat, do you usually shop for it at…?
(1—traditional store (local butcher/delicatessen/shop); 2—local supermarket; 3—indoor and outdoor markets; 4—street markets; 5—big chain supermarkets (Mercadona, Consum, Caprabo, etc.); 6—large-scale hypermarkets (carrefour, Alcampo, etc.); 7—others)
7. Thinking only about turkey meat-based preparations (burgers, sausages, sliced, marinated, etc.) Do you usually …?
(1—traditional store (local butcher/delicatessen/shop); 2—local supermarket; 3—indoor and outdoor markets; 4—street markets; 5—big chain supermarkets (Mercadona, Consum, Caprabo, etc.); 6—large-scale hypermarkets (carrefour, Alcampo, etc.); 7—others)
8. Thinking only about chicken meat-based preparations (burgers, sausages, sliced, marinated, etc.) Do you usually purchase it at…?
(1—traditional store (local butcher/delicatessen/shop); 2—local supermarket; 3—indoor and outdoor markets; 4—street markets; 5—big chain supermarkets (Mercadona, Consum, Caprabo, etc.); 6—large-scale hypermarkets (carrefour, Alcampo, etc.); 7—others)
9. And in terms of the purchasing format, how do you usually get your fresh turkey?
(1—whole; 2—in cuts, prepared by the butcher; 3—packaged; 4—others)
10. And in terms of the purchasing format, how do you usually get your fresh chicken?

(1—whole; 2—in cuts, prepared by the butcher; 3—packaged; 4—others)

11. Now, I'm going to read out some criteria and I'd like you to rate the importance of each one when buying turkey (both fresh and prepared) from 1—not at all important to 5—very important:
(1—geographical origin; 2—item appearance; 3—price; 4—butcher's recommendation; 5—information on rearing; 6—manufacturer's brand; 7—retailer/supermarket brand; 8—trust in the place of purchase; 9—organic; 10—nutritional information; 11—others)
12. Now, I'm going to read out some criteria and I'd like you to rate the importance of each one when buying chicken (both fresh and prepared) from 1—not at all important to 5—very important:
(1—geographical origin; 2—item appearance; 3—price; 4—butcher's recommendation; 5—information on rearing; 6—manufacturer's brand; 7—retailer/supermarket brand; 8—trust in the place of purchase; 9—organic; 10—nutritional information; 11—others)

Group 3: consumption habits

1. Can you tell me how often you consume fresh turkey meat in your household?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
2. Can you tell me how often you consume prepared turkey products (burgers, sausages, sliced, marinated, etc.)? In your household?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
3. Can you tell me how often you consume fresh chicken in your household?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
4. How often do you consume prepared chicken products (burgers, sausages, sliced, marinated, etc.)? In your household?
(1—once a week or more often; 2—every two weeks; 3—once a month; 4—once every two months; 5—less than once every two months; 6—never)
5. Which aspects of turkey meat (both fresh and prepare) would you highlight about consuming it?
(1—tasty; 2—quality; 3—healthy; 4—good price; 5—the children like it; 6—easy to make; 7—is part of the diet; 8—others)
6. Which aspects of chicken meat (both fresh and prepare) would you highlight about consuming it?
(1—tasty; 2—quality; 3—healthy; 4—good price; 5—the children like it; 6—easy to make; 7—is part of the diet; 8—others)
7. How do you usually prepare turkey (both fresh and prepared) at home?
(1—grilled/barbecued; 2—fried; 3—breaded; 4—stewed; 5—with sauces (tomato, picadillo, etc.); 6—others)
8. How do you usually prepare chicken (both fresh and prepared) at home?
(1—grilled/barbecued; 2—fried; 3—breaded; 4—stewed; 5—with sauces (tomato, picadillo, etc.); 6—others)

9. Why do you not eat turkey in your household, or not do so more often?
(1—I don't like it; 2—the price; 3—not used to it; 4—because it is difficult to cook; 5—because it takes a lot of time to prepare; 6—others)
10. Why do you not eat chicken in your household, or not do so more often?
(2—the price; 3—not used to it; 4—because it is difficult to cook; 5—because it takes a lot of time to prepare; 6—others)
11. Are there children under 18 years of age living at home?
(1—yes; 2—no)
12. Do the children under 18 eat turkey meat?
(1—yes; 2—no)
13. In what formats would you present turkey meat to make it more attractive to children?
(1—burger; 2—kebabs/skewers; 3—nuggets; 4—croquettes; 5—sausages; 6—sliced cold cut; 7—others)
14. Do the children under 18 eat chicken?
(1—yes; 2—no)
15. In what formats would you present chicken to make it more attractive to children?
(1—burger; 2—kebabs/skewers; 3—nuggets; 4—croquettes; 5—sausages; 6—sliced cold cut; 7—others)
16. Between turkey and chicken meat, which of them is the one that, according to you, most fits what is indicated in the following statements: (1—turkey; 2—chicken; 3—both)? A—it's a clean and healthy meat; B—it is easy to find in the premises where I do my shopping; C—good value for money; D—it is tasty meat; E—meat that is easy and quick to cook; F—high quality meat; G—can be prepared in many ways; H—it's digestive, it's not heavy; I—it is an attractively priced, economical meat

Group 4: food lifestyles

1. Now, I'm going to read out a series of statements about shopping behaviour and I'd like you to rate them from 1 strongly disagree to 5 strongly agree. A—I like to read the food product labels and know their composition; B—advertising helps me decide which foods I'm going to buy; C—I like doing my household food shopping; D—I like shopping in specialist stores where they can advise me; E—I keep an eye on the changes in price of the foods I usually buy; F—I usually decide what I'm going to buy when I get to the food shop
2. Now, I'm going to read out a series of statements about qualitative aspects and I'd like you to rate them from 1 strongly disagree to 5 strongly agree. A—I prefer to buy natural products, e.g. preservative-free products; B—I always try to get the best quality at the best price in foods; C—I like to try new foods; D—I like buying organic products if I have the chance; E—I think it's more important to choose food products for the nutritional value rather than their flavour; F—I prefer fresh products to canned or frozen
3. Now, I'm going to read out a series of statements about ways of cooking and I'd like you to rate them from 1 strongly disagree to 5 strongly agree. A—I like to spend a lot of time cooking; B—I like cooking and experimenting with new recipes; C—at home we normally use ready to eat foods such as salads; D—the family gets involved in preparing meals; E—I often decide which

foods to prepare at the last minute; F—the woman is responsible for achieving a healthy and nutritional diet for the family

4. Now, I'm going to read out a series of statements about ways of cooking and I'd like you to rate them from 1 strongly disagree to 5 strongly agree. A—I prefer snacking rather than a formal meal; B—I like going to restaurants with family and friends
5. Now, I'm going to read out a series of statements about reasons for choosing foods and I'd like you to rate them from 1 strongly disagree to 5 strongly agree. A—I find cooking very satisfying; B—I only buy and eat products that are familiar to me; C—I feel that sharing a meal with friends and family is an important part of my social life

GROUP 5: identification data

1. How many people live the household, including you?
2. Could you tell me the number of inhabitants in the municipality where you live?
(1—fewer than 10,000; 2—from 10,001 to 50,000; 3—from 50,001 to 100,000; 4—from 100,001 to 500,000; 5—over 500,000)
3. Can you tell us your educational qualifications?
(1—no schooling; 2—primary education; 3—lower secondary education; 4—upper secondary or postsecondary education; 5—tertiary education)