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Methodological Strategies for the development of a Meat Probiotic Product based on Data Science using consumer studies

Metodología de estudio para el desarrollo de un producto cárnico probiótico empleando ciencia de datos con consumidores

Domínguez-Soberanes, J.[a,c], Rodríguez-Serrano, G.[d], Sánchez-Gutiérrez, G.G.[a], Sánchez, C.N.[b], Ortega-Caín, O.[a], Chávez-Vela, N.[c], Escalona-Buendía, H.B.[d]

[a] Universidad Panamericana. Escuela de Dirección de Negocios Alimentarios. Josemaría Escrivá de Balaguer 101, Aguascalientes, Aguascalientes, 20296, México.
[b] Universidad Panamericana. Facultad de Ingeniería. Josemaría Escrivá de Balaguer 101, Aguascalientes, Aguascalientes, 20296, México.
[c] Universidad Autónoma de Aguascalientes, Departamento de Ingeniería Bioquímica, Av. Universidad 940, Ciudad Universitaria, Aguascalientes, Ags., 20131, México.
[d*] Universidad Autónoma Metropolitana Iztapalapa, Departamento de Biotecnología, San Rafael Atlixco 186, Vicentina, Iztapalapa, 09340 Ciudad de México, D.F.
jdominguez@up.edu.mx; gmrs@xanum.uam.mx; 0171350@up.edu.mx; 0173183@up.edu.mx; nachavez@correo.uaa.mx; hbeb@xanum.uam.mx

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Resumen

El análisis sensorial juega un papel decisivo para determinar si el consumidor aceptará o no un nuevo producto que va a ser lanzado al mercado. Esto es de importancia, tomando en cuenta que más del 50% de los productos desarrollados salen del mercado en el primer año de vida del producto. Por lo tanto, se requiere un análisis más preciso, y una herramienta para lograrlo es el uso del análisis del aprendizaje automatizado aunado a las técnicas convencionales de análisis, esta combinación de información nos permite tomar mejores decisiones. La Ciencia de Datos permite tomar respuestas de consumidores para agruparlos y hacer el perfilado de usuarios, además de analizar las preferencias y en su caso detectar los atributos que requieren ser optimizados para mejorar la aceptación de los productos. Por lo tanto, en este estudio, un producto desarrollado de carne probiótico se comparó con otros cinco productos de marcas comerciales líderes en el mercado de Aguascalientes, México.

Los resultados de composición química, nos demuestran que este producto es una buena fuente

de proteína y fibra con bajo contenido en grasa. Mostrando que su composición química es de: 71.93%, 13.59%, 6.74%, 5.19% y 15.06% de humedad, proteína, grasa, cenizas y BEEFE.
La novedad de esta investigación se basa en el uso de la ciencia de datos, que se convierte en una parte importante para integrar distintos análisis de datos y estadísticos para analizar la información de consumidor a fin de proveer un mejor entendimiento del nuevo producto alimenticio diseñado desde el punto de vista sensorial. Por lo tanto, los productos cárnicos fueron analizados sensorialmente por 72 consumidores y se aplicaron distintos métodos y metodologías relacionadas con análisis sensorial, las cuales fueron analizadas mediante diferentes análisis estadísticos y de aprendizaje automatizado. Estos se llevaron a cabo haciendo uso de dos diferentes pruebas a consumidores o afectivas: justamente correcto (por sus siglas en inglés, JAR), además del estudio de marca todos los atributos que encuentres (por sus siglas en inglés, CATA). Ambos JAR y CATA, analizados establecieron que el prototipo está cerca de lo óptimo de acuerdo a los atributos estudiados y con atributos sensoriales considerados como positivos.

Los resultados de diferentes análisis realizados a las distintas pruebas sensoriales nos indicaron que para el prototipo desarrollado se presentaron buenos resultados que podrían hacerlos competitivos en el mercado. En el análisis de segmentación (por sus siglas en inglés, LSA) mostraron que el producto desarrollado se encuentra cerca de una zona considerada como óptima por los consumidores, lo cual va de acuerdo a otros análisis como él desarrollado por este grupo de trabajo conocido como LPL. En este último se utilizan las escalas hedónicas y JAR para hacer un perfilado de usuarios, y en base a estos, poder determinar las preferencias de los consumidores, y si estás están determinadas por grupos de consumidores. Además de que también se pueden identificar los atributos que deben ser optimizados para mejorar la aceptación de los productos. Los modelos de agrupamiento jerárquico y de mezcla Gaussiana mostraron dos segmentos de posibles consumidores de acuerdo a datos sociodemográficos.
Lo anterior nos demuestra que el realizar este tipo de análisis de datos basados en el análisis sensorial de consumidores obtenemos información complementaria; por otro lado, al utilizar Ciencia de Datos podemos establecer que podemos obtener más información. Lo cual hace que este tipo de metodología de análisis sea adecuada para potencializar el lanzamiento de un nuevo producto a los distintos puntos de venta.

Palabras clave: Análisis de Segmentación, Análisis Sensorial, Ciencia de Datos, Justamente Correcto, Marca todos los atributos que encuentres.

Abstract

Sensory analysis plays a decisive role in determining whether the consumer will accept a new product to be launched into market. This is of importance, considering that more than 50% of the developed products fail in market during the first year of the product's life. Therefore, a more accurate analysis is required, and one tool to achieve this is the use of machine learning analysis in conjunction with conventional sensory statistical analysis techniques. This combination of information will allows us to make better decisions. Data science permits taking responses from consumers to group them and to profile users, as well as to analyze preferences. It detects attributes that need to be optimized to improve product acceptance. Therefore, in this study, a developed probiotic meat product was compared with five other products from leading commercial brands in the market of Aguascalientes, Mexico.

The chemical composition results show that this product is a good source of protein and fiber with low fat content. Showing that its chemical composition is 71.93%, 13.59%, 6.74%, 5.19% and 15.06% of moisture, protein, fat, ash and BEEFE.

The uniqueness of this research is based on the use of data science, which becomes an important part to integrate different data in order to analyze consumer information for providing a better understanding of the new designed food product from a sensory point of view. Therefore, the meat products were sensory analyzed by 72 consumers and different methods and methodologies related to sensory analysis were applied. Data was analyzed by different statistical and machine learning techniques. These were carried out using two different consumer or affective tests: just right (JAR), in addition to check all that apply (CATA) study. The analysis of both JAR and CATA established that the prototype is close to optimal according to the attributes studied. Moreover, the sensory attributes were considered to be positive.

The results of different analyses carried out on the different sensory tests indicated that the prototype developed showed good results that could make it competitive in the market. The landscape segmentation analysis (LSA) showed that the developed product is close to a zone considered as optimal by consumers, which is in accordance with other analyses such as the one developed by this working group known as LPL (Liking Product Landscape). In the latter, hedonic and JAR scales are used to profile consumers and, based on these, to determine consumer preferences and whether they are determined by consumer groups. In addition, attributes that need to be optimized to improve product acceptance can also be identified. The hierarchical clustering and Gaussian mixture models showed two segments of possible consumers according to socio-demographic data.

The above shows us that by carrying out this type of data analysis based on consumer sensory analysis we can obtain complementary information. On the other hand, by using Data Science we can establish that we can obtain more information. This makes this type of analysis methodology suitable to assure success of a new product in the market.

Keywords: Check-all that apply (CATA), Just about right (JAR), Landscape Segmentation Analysis (LSA), Liking Product Landscape (LPL), Data Science (DS).

I. Introduction

Consumers are looking for food products that are tasty, easy to prepare and can offer not only a nutritional claim but can offer a health-promoting feature (1, 2, 3). Meat is nutritionally ideal for human consumption, as it is a good source of protein, minerals (iron, zinc, selenium and phosphorus) and vitamins (B complex). One of the problems when consuming meat is its fat content, however, this issue has been solved due to the animals' diet and through genetics, making the product leaner (4,5). In addition, attempts have been made to make processed meat healthier by taking into consideration its formulation process by the reduction of fat content, cholesterol, sodium, nitrites/nitrates and by the modification of the fatty acid profile (6). In addition, meat can also be an ideal matrix for incorporating ingredients to develop functional products, in which we can include plant proteins, probiotics, minerals, vitamins, antioxidants, prebiotics and dietary fiber (5). The most commonly used prebiotic in the meat industry, associated with improved health (7) is chicory inulin, which contains chains of fructose and that is extracted from chicory root, garlic and onion (8, 9, 10).

Therefore, there is a growing opportunity in Food Research and Development (R&D) to design meat products that could be healthier and could meet sensory needs (11). In addition, they have the appropriate sensory characteristics that consumers are looking for.

There is also a growing need for precise and faster types of methods for evaluating food chemical composition and Near Infra-Red (NIR) is one of them (12, 13, 14, 15, 16).

On the other hand, a proper exploration of consumers' perception and insights are determinant to increase the possibilities of a successful product development. Landscape Segmentation Analysis (LSA) is a technique based on both consumers liking and analyzed products. Consumers' evaluations are plotted on a sensory map, where dark contours indicate ideal consumers' segments that refer to different marketing groups. This technique makes it possible to compare newly developed products with existing products on the market, establishing through a sensory map how close or far they are regarding consumers' expectation (17, 18, 19). Liking Product Landscape (LPL) is a methodology in which several maps represent the consumers' distribution and their evaluations. However, it differs from LSA, because instead of superimposing the overall average liking within one map, it uses different maps for the evaluation of each consumer (20, 21).

Another sensory technique used in food development, involves the use of JAR (Just About Right). Consumers establish if whether the attribute of each product is JAR, or if it has less or more intensity based on their expectation (17). This technique has been used in R&D, for example, to establish the amount of stevia needed in a vanilla yogurt (22). Some research has used JAR to optimize the acceptability of low-fat dairy beverages with different types of inulin, when analyzed with a surface response methodology (23). One option is to analyze the data obtained through JAR through Thurstonian analysis; where d' is calculated. This value refers to the distance between means taking into consideration the standard deviation. It can establish differences between the new formulation and the optimal product (17).

In addition, another sensory analysis test used in R&D is known as CATA (Check all that apply), which is a tool that can detect positive and negative attributes present in products. CATA is used as an alternative to JAR. However, JAR scales are more accurate in establishing differences from the optimal than CATA questions. It is important to mention that for R&D, CATA questionnaires are of increasing interest. In addition, different approaches have been proposed for obtaining and analyzing these data in order to achieve a more accurate profile of consumers (24, 25, 26). After performing CATA analysis, contingency tables can be generated, in which rows refer to the stimuli analyzed, and the columns describe the attributes present in the products (27).

Decision trees with continuous classes, where a regression model is fitted to predict values of Y (28), in this case, the acceptance of a product. There are studies that evaluate the influence of perception and liking. For example, one research consisted in asking in a food exhibition to evaluate different cheese products using a RATA (Rate all that Apply) based on a JAR (Just about Right) Scale (29). Perception was then analyzed through methods such as classification and regression trees. The information allowed the influence of perception on attributes to be investigated, which was useful to identify the main drivers of liking.

Sensory analysis is a science that applies statistical analysis, which is evolving in its methods. Thus, the novelty of this work is that in addition to the use of the above-mentioned methods and methodologies, our purpose is to provide more information for R&D. For example, we can focus on Data

Science techniques in order to have complementary information and make better decisions when launching a product into market. Let us start by describing latent components which are non-directly observable variables, but these can be inferred by visible variables that are correlated with each other and some of their uses are for segmenting different market groups and liking attributes (30**,** 31). In addition, other methods used in sensory analysis are K-means, Hierarchical Clustering and Gaussian Mixture Models (GMM).

The K-means clustering (32) is a commonly used method to divide data sets into k groups. Some of the reported uses of K-means is to group food products according to different attributes (33, 34). Hierarchical clustering analysis refers to the use of a data analysis procedure that generates a classification for data sets (35); one of its uses is to group panelists (36).

A Gaussian mixture model is a parametric probability density function represented as a weighted sum of Gaussian component densities (37). GMM has been useful to find segments in sensory analysis (38). In a recent study, evaluating food products such as tomatoes, wine and apples, it was found that sensory quality cues were important and that sensory descriptions were preferred over other characteristics such as variety names or sensory labels (21).

This research aims to determine the acceptance of the consumers in Aguascalientes, México; regarding a prebiotic meat prototype that was designed in our lab, which was compared with five leading commercial products, analyzing their chemical composition. For this, we used different sensory statistical approaches such as LSA, LPL, Thurstonian d' values, contingency tables, hierarchical clustering, Gaussian mixture models and decision trees. Our hypothesis is that: 1) the use of different types of methods and methodologies can be used to compare and complement each other and 2) The use of data science is an ally in sensory analysis in order to guarantee new product success in market. Therefore, it could be used as a new approach during the first stages for launching new products into the market.

II. Material and Methods

The methodology followed in this research is set out in Figure 1, each step of which will be explained in the following sections.

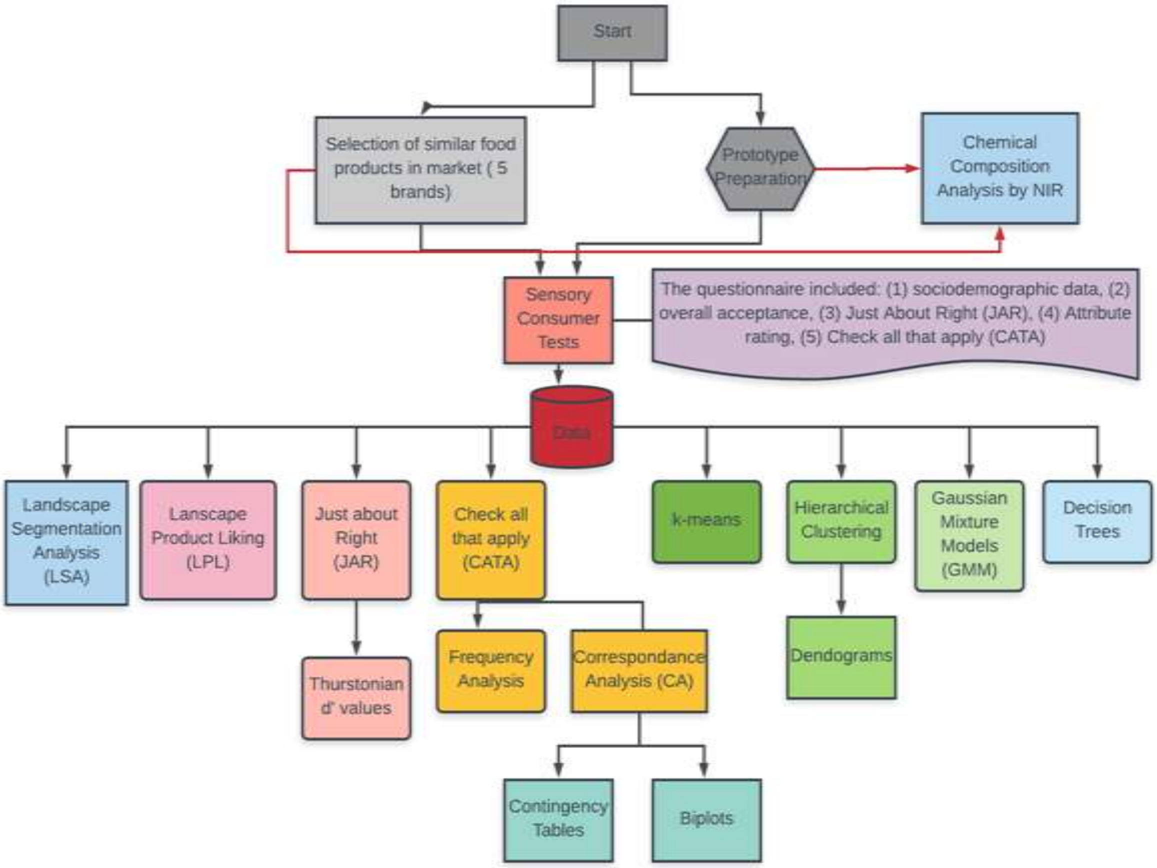


Figure 1. Methodology.

II.1. Prototype formulation

A ready to eat pork prebiotic product (Product 1) was designed in our lab, by preparing the marinade mixture according to Table 1. All the ingredients were mixed in hot water for 10 minutes. The marinade mixture was then combined with the chicory inulin and incorporated into the pork loin, which was previously cut into pieces of 3 x 3 cm (Empacadora de Carnes San Francisco, S.A., Aguascalientes, Mexico). This mixture was placed in a rotary drum (Flavor Maker F-8, USA) during 15 min at 15 mm of Hg, and then vacuum-sealed (Smartvac Mini 28, Carnotex S.A. de C.V., Mexico) at 18 s with 0.75 bars. Sous vide cooking technique was applied in a runner (Sirman Mod. Softcooker y09, Italy) for 3 h at 60°C. Finally, the samples were cooled and refrigerated at 3 ˚C.

Table 1. Ingredients used for the Prebiotic Ready to eat pork product (Product 1).

	Percentage (%)	Ingredient	Percentage (%)
Meat	81.50%		
Marinade	15.8%	Water	70.76
		Jamaica (*Hibiscus*)	3.98
		Oil	5.75
		Onion	0.40
		Garlic	0.66
		Rosemary (*Rosmarinus officinalis*)	0.27
		Commercial Marinator	0.60

		Chipotle (Dried Chili)	4.42
		Vinegar	2.87
		Salt	5.66
		Peppers	2.12
		Chicory Inulin (Orafti, USA)	2.50
Chicory Inulin (Orafti, USA)	2.60%		
Total	100.00%		100%

The other formulations used in this study refer to leading brands in Aguascalientes, México (Brands 2-6). Products 2, 3, 5 and 6 were bought in grocery stores; while, Brand 4 was purchased in a butcher shop in Aguascalientes México.

II.2. Composition Analysis by NIR

Samples bags of 20 g were placed into the petri dish of the Near Infrared Equipment (FT-NIR Buchi NIR Master, Switzerland), which is a spectrophotometer with a wavelength in a range of 800-2500 nm. After introducing the sample into the equipment, the following was obtained: humidity, fat, protein, connective tissue, ashes and BEEFE. The last refers to the bioavailable protein, which is calculated by subtracting connective tissue protein from total protein (BEEFE = Protein - connective tissue protein). Three analysis were performed by triplicate, obtaining nine results. Finally, the results were analyzed by ANOVA and a Tukey's difference test ($\alpha \leq 0.05$) was applied in order to identify the products that are different for each parameter studied with XLstat ®, Addinosoft 2015.

II.3. Sensory Consumer Tests

II.3.1. Consumers' characteristics

Based on previous studies, we noticed that consumers in Aguascalientes, México, who are in their 20s and 30s, are the most likely to consume prepared or ready to eat products (39). Therefore, this study is based on young people, mainly students. Seventy-two people at Universidad Panamericana in Aguascalientes, México, were told that the data obtained from this research would be used for a research project to be published. Therefore, they were asked to respond to a sensory questionnaire, which instructions were explained at the beginning of the test. Almost half of the subjects were male and more than 90% consumed pork on a regular basis.

II.3.2. Sociodemographic information

Consumers filled in some additional information before answering the sensory test, such as age and gender (sociodemographic information). Regarding their consumption habits, they were asked if they consumed pork and how often they did so. In addition, they were asked whether they consumed spicy products (chili). Consumers also answered whether they ate out and how often per month they did so.

II.3.3. Sensory Test

This analysis was based on the ISO 11136-2014 (40), which establishes the methodology for conducting sensory tests for consumers in a controlled area. The perception of products by consumers is the main factor when taking into consideration that they hold the purchase decision. For these purpose, pieces of pork loin (30g) were presented at an average of 37ºC in a sensory cabin in which subjects were asked to taste from right to left each of the six different samples offered. One of these, developed for this research, and five more that were purchased from local markets, in the same way as in other studies (41). Water and crackers were offered after tasting each of the products, and the light was monitored. Sensory testing was conducted in a single session.

The first steps for launching a product into market are based on product acceptance testing, which is considered the first stage in the product development process. Therefore, consumers tested different products in a given sequence, followed by a result on their sensory appreciation. It is important to point that product intake is interrupted by breaks in which subjects neutralize their senses with water and crackers (42).

Each consumer received an evaluation sheet. The questionnaire was divided into sections where overall acceptance, JAR, attribute rating and a CATA, were evaluated. Beforehand, consumers were explained in detail the process for completing the test. Consumers took between 10-15 minutes to answer the evaluation. The consumer's decision depended on the sensory attributes of the products according to Morais et al. (43).

II.3.3.1. Overall acceptance

First, consumers evaluated the overall acceptance of the product on a scale ranging 1 to 10, where 10 represented the highest mark.

II.3.3.2. Just About Right (JAR)

Consumers were asked to establish whether some attributes were Just About Right (JAR) or had more or less of the studied attribute.– JAR refers to the center of the scale, to the right too much of a certain attribute and on the left low intensity of each attribute studied. A group of 12 students form the Business Gastronomy Major who had received previous training in sensory science were invited to establish the most relevant sensory attributes in the designed product. Thus, the attributes evaluated were odor, color, acidity, chili sensation, salt, flavor, juiciness and texture. Finally, participants were asked to rate liking using a 5-point hedonic scale.

II.3.3.3. Attribute rating

Each attribute was rated on a scale ranging 1 to 10, where 10 represented that the attribute had the acceptability. The attributes studied were odor, color, acidity, spiciness, saltiness, jamaica (*Hibiscus*) flavor, juiciness and texture.

II.3.3.4. Check all that apply (CATA)

The CATA test (Check all that apply) based on ten descriptors was analyzed. The descriptors were obtained in a sensory session, where 12 students from the Major of Business Gastronomy who had received previous training in sensory science were invited to establish the most relevant ones. Five of the descriptors were considered positive: spicy smell, chipotle flavor, adequate firmness, natural color and juiciness. The other five descriptors took into consideration negative factors such as oxidative color, dryness, acidity, insipid taste and pasty.

3. Data Analysis (Calculations)

III.1. Landscape Segmentation Analysis (LSA)

Consumers were asked to rate the overall acceptability and attributes in a 1 to 10 scale. The attributes studied were odor, color, acidity, chili sensation, salt, flavor, juiciness and texture. The ratings obtained were analyzed through IFPrograms™, obtaining a Landscape Segmentation Map (LSA) where the optimal zones can be established and the products tested can be located. In addition, the effect of liking on each of the studied attributes can be obtained, establishing correlations and statistical differences ($\alpha \leq 0.05$).

III.2. Liking Product Landscape (LPL)

The LPL was used to compare the overall liking between products and to analyze the perception of all attributes (odor, color, acidity, chili sensation, salt, flavor, juiciness and texture) specifically of the developed prototype developed as established by Sánchez et al. (44). The source code of the LPL methodology can be found in the GitHub repository (45).

III.3. Distance matrix of consumers' grades

In order to find groups of consumers a number of techniques were applied. First the distance matrix of consumers' overall acceptability ratings, on the scale 1 to 10, was performed. The square distance matrix was composed of 72 rows and 72 columns, where each cell (i,j) represents the Euclidean distance between the vector composed of consumer i´s 6 product ratings and the vector composed of consumer j´s 6 product ratings. In other words, cell (i,j) represents the rating difference between the consumer i and j.

III.4. Hierarchical clustering (Dendrogram)

Another technique to explore groups was Hierarchical clustering with the distance matrix as a fusion strategy, observing that with the generated dendrogram it is possible to observe similarities or differences among consumers' overall acceptance ratings. Both the distance matrix and hierarchical clustering were performed with Python.

III.5. Gaussian Mixture Models (GMM)

Gaussian Mixture Models (GMM) was used to find consumer groups based on ratings in the scale 1 to 10 of the overall acceptance. GMMs were used because they use Gaussians functions for each group and give more flexibility than hyperspheres used in k-means. It was performed with Python.

III.6. d' Calculations for JAR scaling

The Thurstonian model was used to obtain d' values that indicate how far each sample is from the optimum by measuring the distance between means in terms of standard deviation (17). Results were analyzed using IFPrograms™ (USA), and with graphs created in Python showing the percentage of JAR for each attribute studied.

III.7. Frequency analysis for CATA test

The consumers were asked to tick if any of the ten parameters (5 positive and 5 negative) was perceived. With this information, a frequency analysis was done, followed by a Correspondence Analysis (CA), which was calculated with XLstat®, Addinosoft 2015, generating information such as contingency tables and biplots.

III.8. Decision tree

A regression decision tree was performed to visualize the relationship between the consumers' preference and their demographic information. The input to the algorithm was consumers' demographic data and the output was consumers' ratings. This process was performed in Python.

III.9. Programs used for Statistical Analysis

Landscape Segmentation Analysis® was analyzed using IFPrograms™, ANOVA of chemical parameters, contingency tables and CA biplots were performed with XLstat®, Addinosoft 2015.

Decision trees, Dendrogram, Gaussian Mixture Models (GMM), percentage graphs of JAR and Distance Matrix of Consumers' ratings were performed using Python.

IV. Results and Discussion

In this study, a meat product prototype (Product 1) was designed with the objective of generating a nutritional product with appropriate sensory characteristics, because both variables are decisive in achieving willingness to purchase food products (46, 48).

In food development, inulin has shown great potential because it is associated with health benefits (46). Furthermore, as an ingredient, when inulin is added at 1% it works as a fat substitute that contributes to a better mouthfeel by increasing the flavor and decreases the caloric value of the product. Previous studies have added inulin to chicken breasts marinades, increasing the nutritious value without altering the sensory properties (9). For the prototype (Product 1), inulin was incorporated in a 2.8% of its formulation, so it could be considered a fiber-added product according to Mexican Regulations (47) which establish that if the fiber added content is 2.5g/100g it can be considered this type of product. However, even when the prototype is nutritious, it is important to evaluate its sensory properties in order to guarantee success of the product launched into the market based on the product liking (46, 48). In addition, to provide a better overall liking of the prototype, the product was cooked with a technique known as *Sous Vide*, because it maintains and improves the physicochemical and sensory characteristics of products (49).

The developed prototype (Product 1) and the other five brands were analyzed for their composition using the NIR (Near Infrared) System; the results are presented in Fig 2. The results show that the brands that have the highest humidity content ($\alpha \geq 0.05$), which is associated with palatability are number 6 and 5; followed by 1 and 3. The lowest humidity was observed in brand 4 followed by brand 2. Therefore, it is likely that the developed prototype may have this sensory characteristic. The results (Figure 2) show that products 1 and 6 had less fat ($\alpha \geq 0.05$), which means that the developed prototype has a great advantage for consumers requesting this type of product.

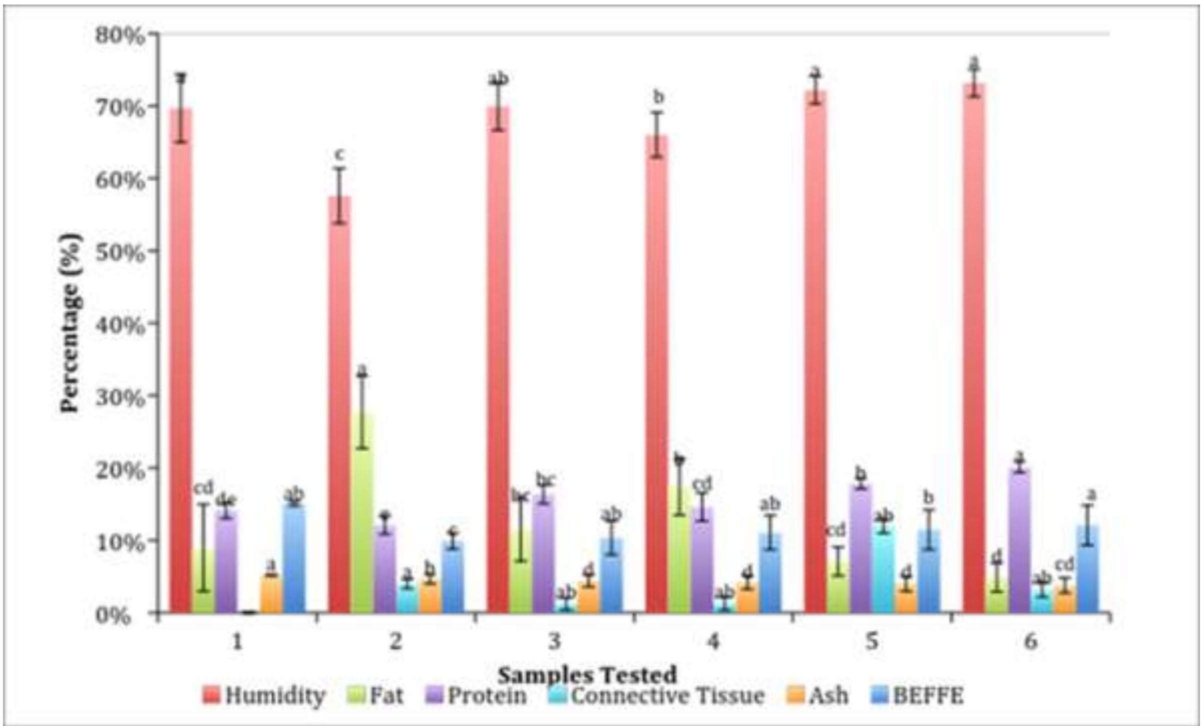


Figure 2. Analysis of the chemical composition of products (Humidity, fat, protein, connective tissue, ash and BEFEE) by Near Infrared (Buchi, Switzerland) of the 6 products studied. Product 1 refers to the prototype developed in the lab, and products 2 to 6 refer to leading brands in Aguascalientes n=9.

When analyzing proteins (Figure 2), brand 2 showed the highest value, however when analyzing the BEEFE results which refers to the protein that can be bioavailable, the highest values ($\alpha \geq 0.05$) were found in Brand 6, followed by Product 1 ($\alpha \geq 0.05$). When analyzing the chemical composition of the prototype (Product 1), we can establish that it can be considered a good source of protein. The complete chemical composition measured by NIR, gave the following values: 71.93%, 13.59%, 6.74%, 5.19% and 15.06% of humidity, protein, fat, ashes and BEFFE respectively. Meat is a great source of protein and fat; it also provides with vitamins and minerals that can be observed with these results (50). Furthermore, it can be observed that the type of meat has influence on the characteristics of the product; the prototype was elaborated by pork loin with around 4.27 ± 0.4 % minerals (14, 15 and 16). Moreover, it is important to consider that marinade ingredients have an influence on the chemical composition of the product.

However, as already established, even when the composition of the formulations is important, consumers' acceptability regarding the sensory perception is decisive. Consumers are looking for nutritious meals but are not willing to sacrifice flavor (2). However, in order to be successful in the market, it is necessary to have a better understanding of consumers taste. This means accurate and appropriate analysis of the sensory data, combining sensory and consumer research with statistical treatment of sensory data (51). In the last few years, new methods and approaches have evolved that can give us more information by asking consumers their perception (52, 53). In this study we analyzed the data through Landscape Segmentation Analysis (LSA), Landscape Product Liking, Hierarchical product clustering, distance matrix, d' after JAR, Check-all-that-apply (CATA), frequency and its correspondence analysis, and decision trees. Each of these can provide complementary information based on their strengths and limitations, which are discussed in this research. Therefore, when making a decision in order to launch food products into the market we have to take into consideration a complete analysis, in which each of these can provide us with an integrated information of the food product.

LSA reveals several optimal regions that are represented as dark zones (Fig. 3), showing the distribution of liking ratings for each of the consumers studied (17). Results reveal that the prototype developed (Product 1) is near to one of these dark zones, which means that it satisfies only one consumer segment. It is important to observe that other products are near to other darker segments, which can be considered optimal zones; and product 2, 4 and 6 are positioned there. Product 3 and 5 are far from the optimal zones. In LSA, each attribute can indicate a taste driver of liking which has a statistical effect on the acceptance of different food products, and which are situated in this type of map. The IFP program represents the information in a 3D, the results only show 5 attributes because they are situated in a 2D. Nevertheless, the results show that all the attributes studied, except odor, flavor and texture have an influence in the drivers of liking of the ($\alpha \geq 0.05$) as shown in Figure 3b and Table 2. Correlation in drivers of liking, which is higher than 0.9 is given by acidity, salt and juiciness.

Table 2. Correlations of drivers of liking with eight attributes studied. Subjects n= 72.

Scale Label	Correlation	p-value
Odor	0.76	0.07
Color	0.87	0.02
Acidity	0.90	0.01
Chili Sensation	0.88	0.01
Salt	0.89	0.01
Flavor	0.72	0.10
Juiciness	0.93	0.00
Texture	0.79	0.05

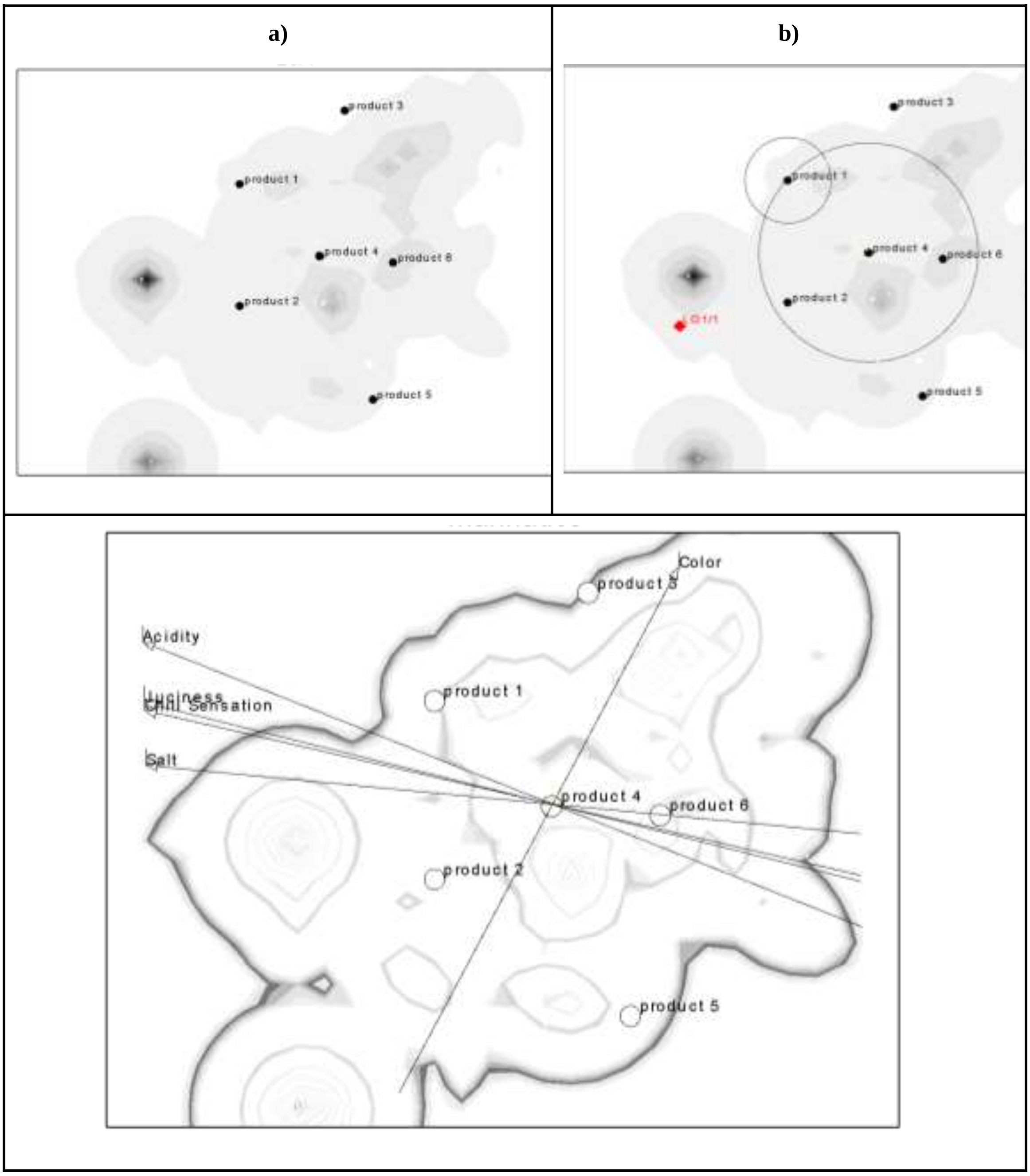


Figure 3. Landscape Segmentation Analysis (LSA) of the six products analyzed, where product 1 refers to the prototype developed for this research. Products 2 to 6 to five are commercial brands. a) LSA b) Portfolio prediction, c) Drivers of liking. Subjects. n= 72.

LSA gives a general idea on how to observe not only consumers and drivers of liking but also products, meaning that the preferred ones are near to a black contour, but the limitation is that the 3D map is set into 2D not giving a good idea on the exact distances between products (17, 18, 19).

Through IFPrograms™ a suggested new product can be recommended based on the drivers of liking and of the existing brands, increasing the portfolio of a food company (Figure 3b). This means that the program can predict where the new development efforts should be focused for this kind of ready-to-eat *Sous Vide* marinade pork products, which is shown as a red dot. It is important to mention that this dot is close to the prototype (Product 1) developed in our lab, labelled as product 1. The developed prototype (Product 1) is positioned with different sensory characteristics, which can be attributed to having a functional character due to its more nutritious character, whereas, products 2, 4 and 6 are similarly positioned according to LSA.

The rating distance among consumers can be observed in Figure 4a. The lighter the color the greater the distance between grading. Therefore, consumers 17, 39, 41, 42, 45, 56 and 57 differ from the rest of the group.

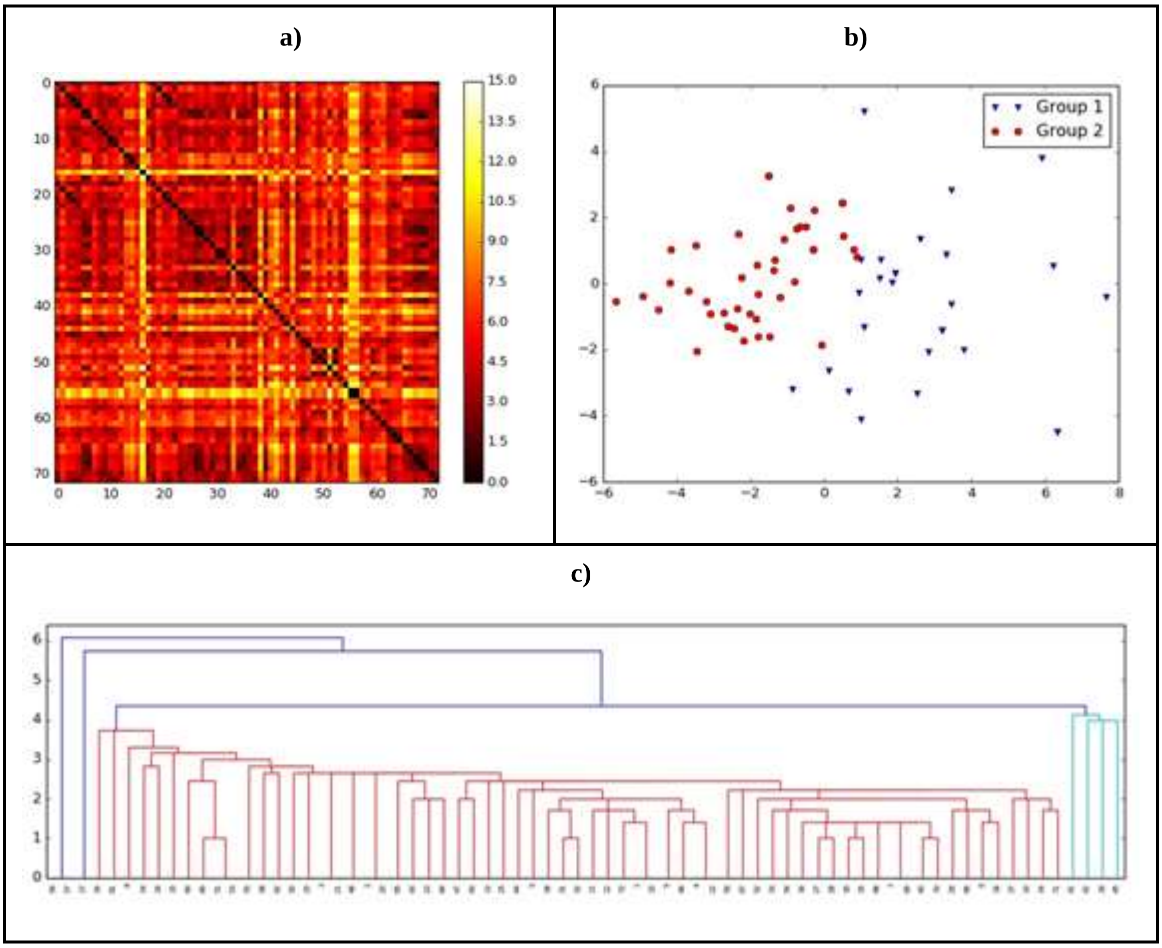


Figure 4. a) Distance matrix between consumer´s grading which evaluated the acceptability value of the 6 products, b) Consumers group in the 2D plane obtained by the first two component of PCA (Principal Components Analysis) applied to integrate the rating of products, c) Hierarchical clustering based on the acceptability values.

Another approach for observing these differences can be obtained by hierarchical clustering (Fig. 4c) where it is possible to observe similarities or differences among consumers' ratings, whose results are in accordance with the ones observed in Figure 4a. Nevertheless, in the hierarchical clustering two different groups of consumers with different colors are observed, the green segment includes consumers: 41, 42, 39 and 45, whereas the red segment is where most consumers are situated. In addition, consumers 17, 56 and 57 graded differently from the rest, and are not considered a group. There are consumers that are evaluated identically (56 and 57), (51 and 53), (3 and 21), (2 and 20), (1 and 19), (4 and 22) and (7 and 69).

Hierarchical cluster analysis (Ward´s Method) can identify groups of consumers by considering its overall liking based on the creation of a dendrogram (54). In our research, we used this type of analysis, in order to know if there were differences between consumers, which can be later correlated with other information e.g. sociodemographic data. Another use of this type of analysis is to identify differences between formulas according to their acceptability where clusters were found (55). A dendrogram can offer a good visual comparison in two dimensions to observe segments, there is research where they compared consumers and a trained panel finding differences between these two groups due to their training. Therefore, this analysis can be applied in different ways depending on the purpose of the study (56). It is also important to correlate grades with their socio-demographic differences as can it be observed in Table 3.

Table 3. Consumers groups according to their sociodemographic data analyzed by GMM.

Group	Age	Gender	Frequency of meat consumption (per week)	Chili consumer	Frequency of eating out (per week)	Frequency of consumption of ready to eat products (per week)
1	25.3± 11.4	F: 68% M:32%	5.9 ± 3.3	Yes: 96% No: 4%	6.4 ± 5.2	7.1 ± 7.0
2	23.5 ± 7.1	F: 30% M:70%	5.9 ± 5.2	Yes: 93% No: 7%	9.7 ± 7.6	4.0 ± 5.2

Table 3. 1. Grades of consumers groups based on their sociodemographic data analyzed by GMM.

Group	Number of consumers	Grades					
		Product 1	Product 2	Product 3	Product 4	Product 5	Product 6
1	28	6.0 ± 1.6	7.2 ± 2.0	4.8 ± 1.8	5.9 ± 1.9	5.4 ± 1.9	7.4 ± 1.9
2	44	8.0 ± 0.9	8.0 ± 1.3	8.3 ± 0.9	7.3 ± 1.0	7.2 ± 1.4	8.4 ± 1.2

These differences can lead to marketing decisions in the food industry, group differences can be determined by gender, and the frequency in which they ate out and consumed ready to eat meals. In the first group, female consumers who ate out on average 6 times a week and consumed ready to eat meals (7 per week) constitute the majority, and rated all products poorly. In contrast, the second group is mainly composed of males who ate out more often (9.7 times per week) and consumed on average less ready to eat meals (4 times per week). The consumer groups are shown in Figure 3b, in which the first two components of the PCA are obtained from the sensory grades of the six products tested.

Principal Component Analysis (PCA) has been widely used in sensory analysis as a visualization technique that reduces dimensionality of data, which means that in a 2D plane most of this information is displayed. It has been the basis for internal and external mapping; some of its uses in sensory analysis is to identify similarities/ differences in grading between attributes, products and judges (19, 24, 31, 50, 51, 52, and 53). In this study, we used PCA, to observe (Fig. 4b) two consumer segments according to the grades given to products.

The Overall liking analysis of LPL can be seen in Figure 5a; the red zones indicate which products are the most liked by consumers; whereas the blue zones are the least liked (44, 57). Therefore, the most liked product is number 6, which has an average linking of 8.0 on a 10-basis scale, followed by Product 2 with 7.7. In third place, we can find product 1, which refers to the prototype developed in our lab, with an average liking of 7.2. Moreover, when we try to understand the influence of the attributes studied in the average liking of the developed prototype (Fig. 5b), we can observe that consumers find the product too weak in juiciness and color. However, the attributes of flavor and texture are high with 62.5% and 65.3% of JAR, respectively.

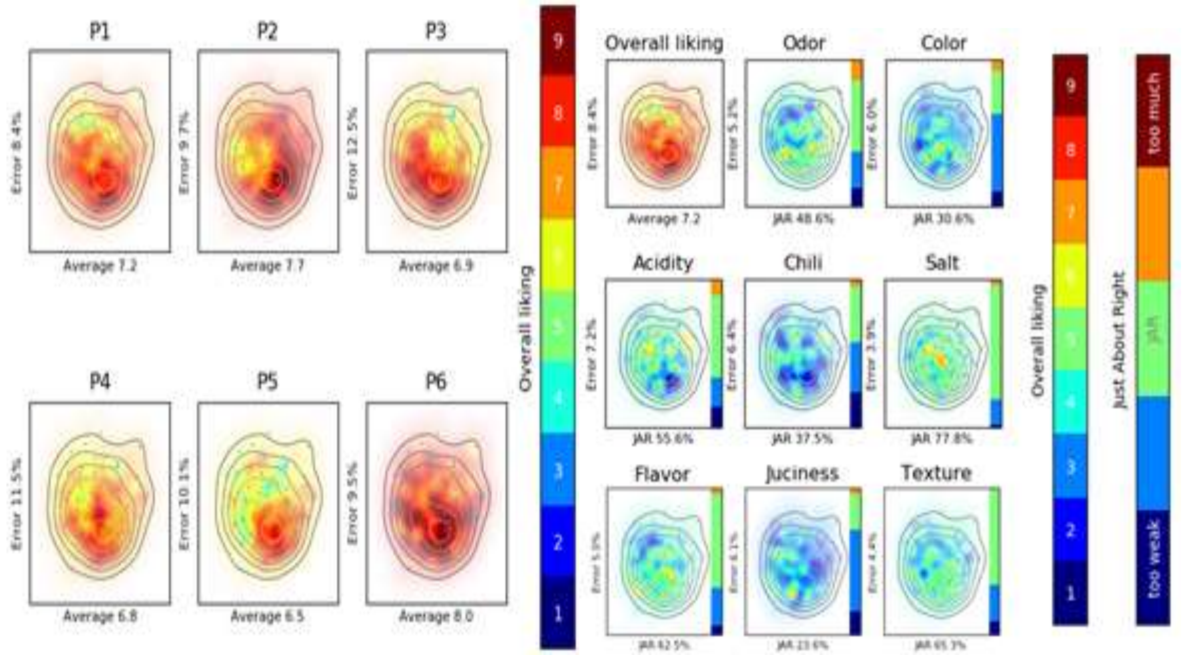


Figure 5. Maps of the Liking Product Landscape. a) Analysis of the Overall Liking comparing the acceptability of the products. b) Analysis of Product 1.

Liking Product Landscape (LPL) is an alternative method that has recently been proposed to visualize consumers' distribution ratings of a specific product, also contours are found for each map that are indicative of market segments. In particular, red contours are indicative of higher rating linking, whereas, the blue ones are the lowest (44, 57). The advantage of this method is that a map is generated for each product, allowing us to examine in detail the information within it. The limitation of LPL, where PCA or MDS is used to create this type of visualization maps, is that the products cannot be represented within it. However, this can be considered as an advantage because it allows a more precise comparison between products. Specifically based on the analysis of overall liking analysis and based on each attribute. Another advantage of LPL is that the consumers of the different maps are always in the same location, establishing how specific consumer segment perceive the attributes studied (44, 57, 58).

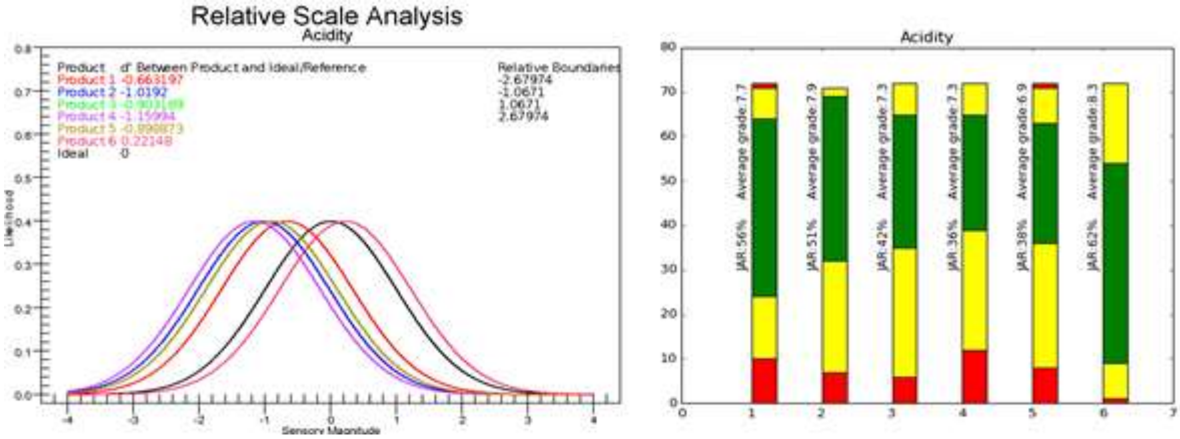
Regarding the JAR methodology (Figure 6), it is important to compare both the JAR frequencies and the d' value, the best results are obtained when JAR is high and d' is near to zero. Taking into consideration the first parameter, the JAR information can also be presented in percentage as shown in Figure 5, where JAR is presented in green and more or less of each attribute is shown in yellow and red. Below the green zone, yellow represents slightly less of each attribute and red represents insufficient quantity of the attribute studied; above the green zone the opposite is shown.

Furthermore, when d' is near to zero, it means that it is closer to the optimum. When analyzing the product developed in the lab, the results obtained for JAR in the different attributes studied were: acidity (56%, d'= -0.66), chili (38%, d'= -1.4), color (31%, d'= -1.12), flavor (62%, d'= -0-06), juiciness (24%, d'= -1.48), odor (49%, d'= -0.61), salty taste (78%, d'= 0.42), texture (65%, d'= -0.9). It is important to mention that in the prototype developed

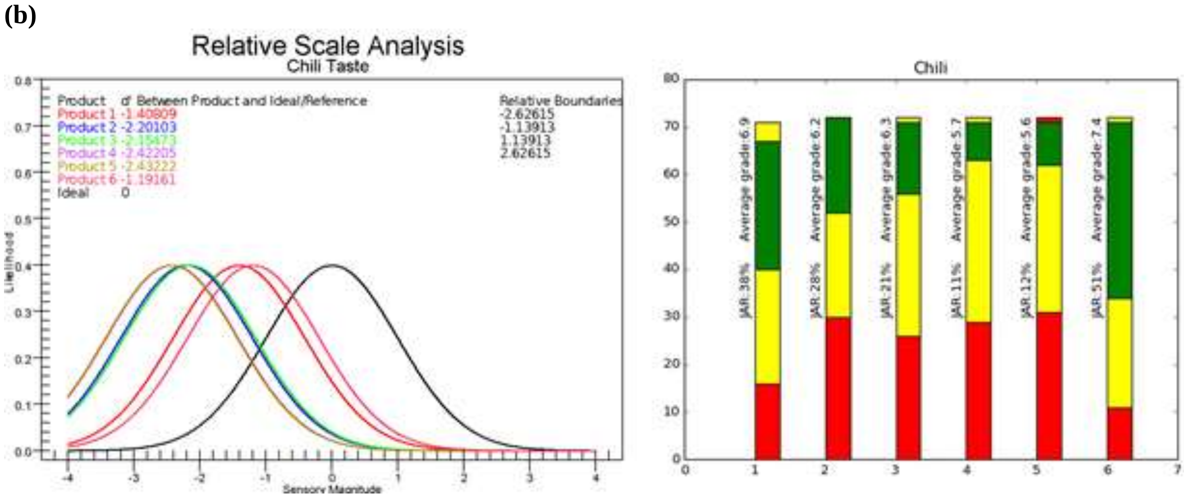
(Product 1), d' values of the other attributes studied were very close to the optimum (0).

Regarding attributes we can observe that chili sensation in all the brands studied was above d'≥1, finding the following values: Prototype (-1.40), brand 2 (-2.20), brand 3 (-2.15), brand 4 (-2.42), brand 5(-2.43) and brand 6 (-1.19). It is important to note that when we analyze the value of d' we can observe that product 6 was the one that was closest to the optimum in all the attributes studied (low value d'), which is in accordance with the results above mentioned.

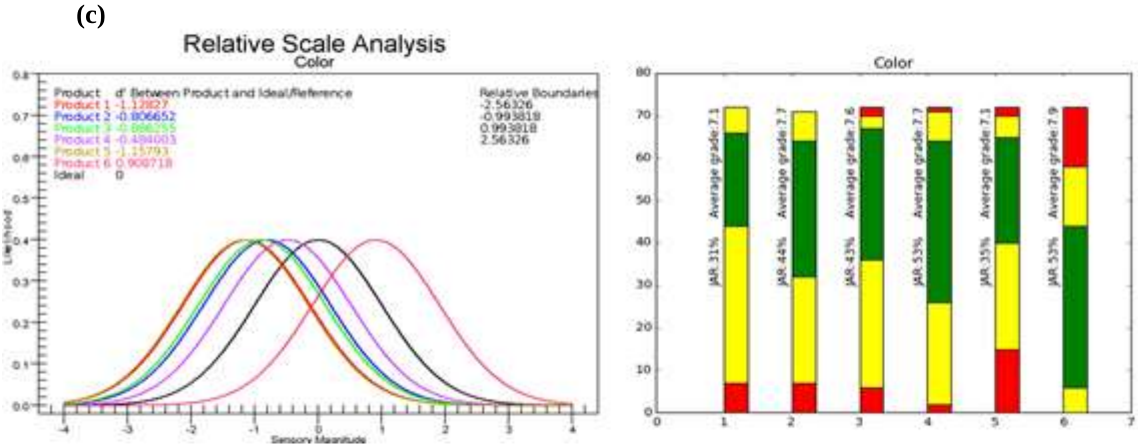
(a)



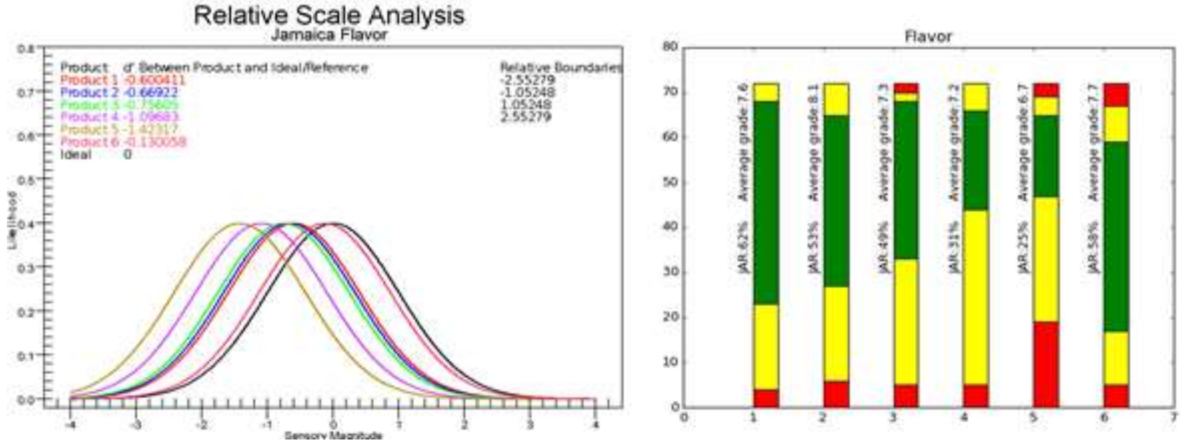
(b)



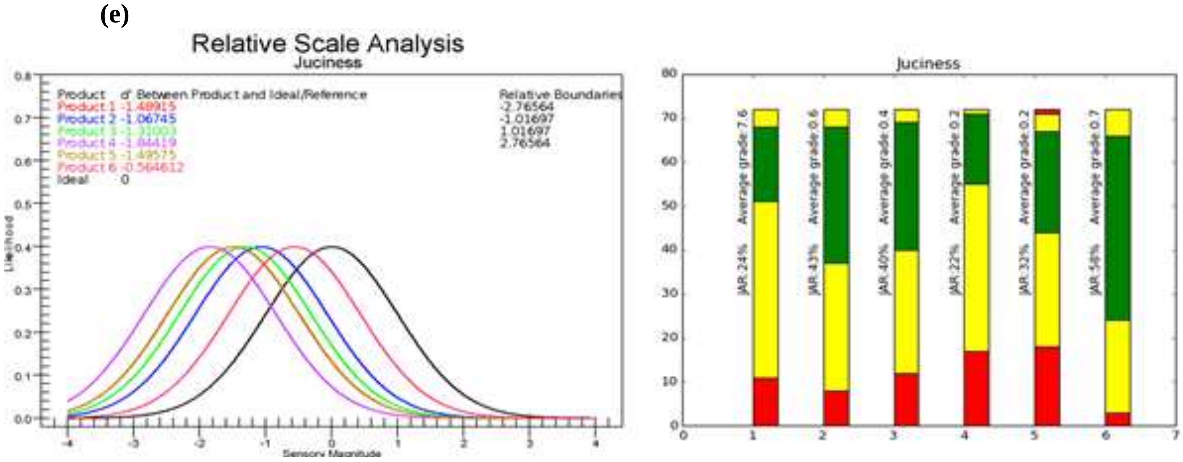
(c)



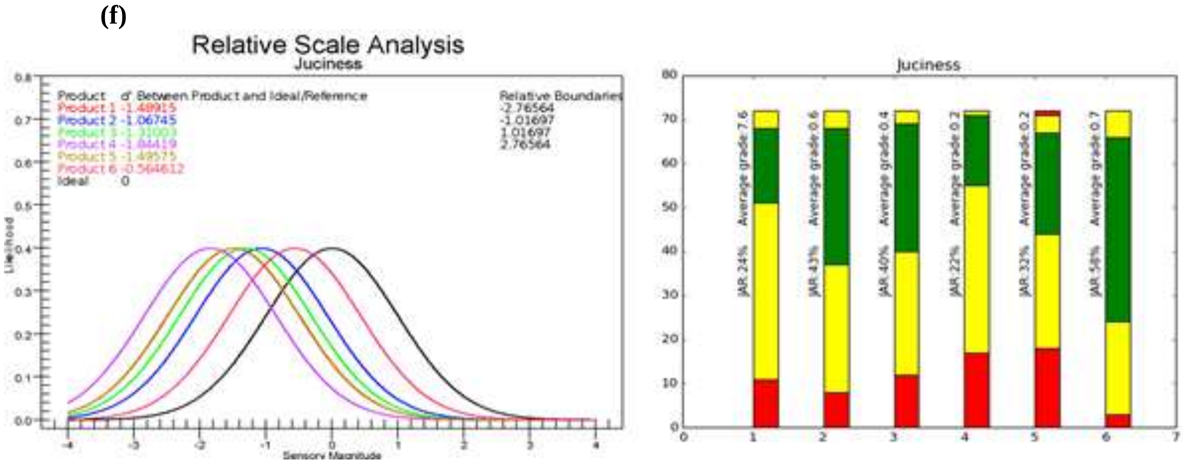
(d)


Relative Scale Analysis
Jamaica Flavor
Product d' Between Product and Ideal/Reference
Ideal 0
Relative Boundaries
-2.55279
-1.05248
1.05248
2.55279
Likelihood
Sensory Magnitude
Flavor

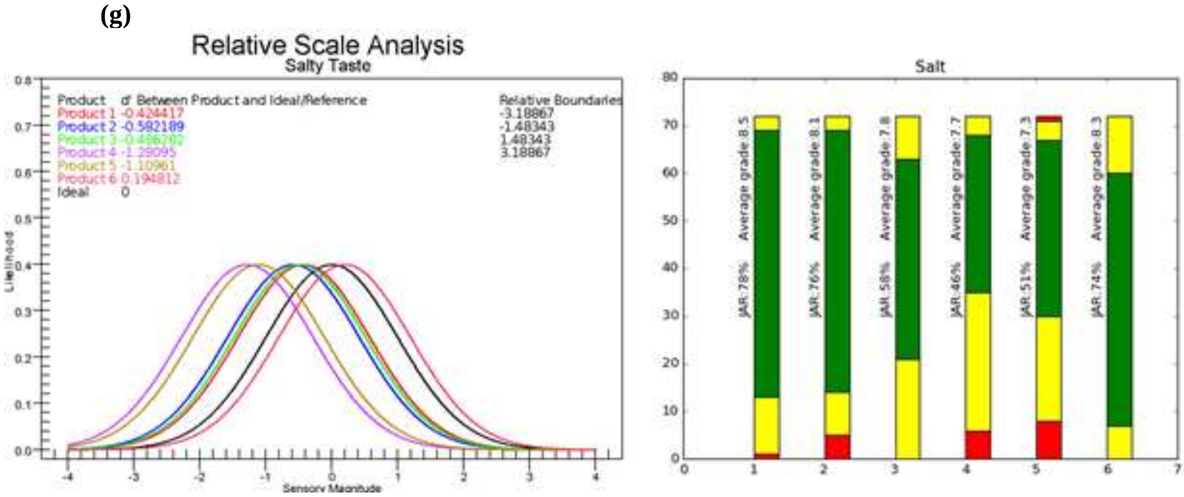
(e)


Relative Scale Analysis
Juciness
Product d' Between Product and Ideal/Reference
Ideal 0
Relative Boundaries
-2.76564
-1.01697
1.01697
2.76564
Likelihood
Sensory Magnitude
Juciness

(f)


Relative Scale Analysis
Juciness
Product d' Between Product and Ideal/Reference
Ideal 0
Relative Boundaries
-2.76564
-1.01697
1.01697
2.76564
Likelihood
Sensory Magnitude
Juciness

(g)


Relative Scale Analysis
Salty Taste
Product d' Between Product and Ideal/Reference
Product 1 -0.424417
Product 2 -0.582189
Product 6 0.194812
Ideal 0
Relative Boundaries
-3.18867
-1.48343
1.48343
3.18867
Likelihood
Sensory Magnitude
Salt

(h)

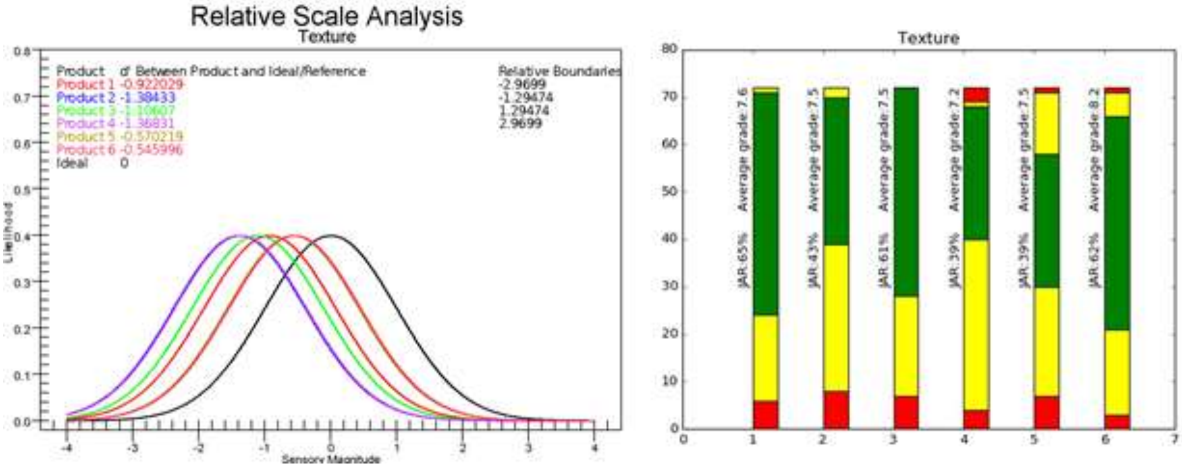


Figure 6. Just About Right (JAR) Test. Left side shows the value of d', which is the deviation of each product in comparison with the ideal point. On the right side, the percentage of JAR is shown. Attributes: a) acidity, b) chili, c) color, d) flavor, e) juiciness, f) odor, g) salt, h) texture. Subjects n= 72.

Just About Right (JAR) can give us information in case of seeking reformulation, as the consumer can establish if the product is JAR or has more or less of an attribute, which is translated into ingredients that could affect liking (59, 60). It is a useful tool for reformulating a product. However, this technique should be used taking into consideration that changing an ingredient could change the overall acceptance of the product (60).

It has been established in previous research (56) that d' values of the Thurstonian model can be defined as the number of standard deviations that depend on the distribution and variance of each stimulus studied. Which means that a value of d' equal to one, is equivalent to one standard deviation which means that there is 100% sensory difference. Results reveal that the d' values of the prototype designed in our lab are less than 1 in most of the attributes studied, which is in correlation with JAR observed for each attribute studied.

The results of the Check All That Apply (CATA) allow appreciating the positive and negative attributes during the sensory evaluation. Our results (Table 4) reveal that the prototype developed in our laboratory was evaluated in the following way: negative attributes represented less than 35% of the CATA in all the attributes studied; whereas positive attributes detected more than 50% of the times showing consistency with JAR values.

Table 4. Check all that apply (CATA) of each one of the brands studied, representing the positive and negative attributes found in each of the prototypes studied. Subjects n= 72.

4.1. Positive attributes

Brand	Natural color	Chipotle Flavor	Good Firmness	Juiciness	Good Odor
1	22%	21%	32%	16%	31%
2	32%	6%	31%	29%	23%
3	32%	9%	35%	20%	32%
4	22%	8%	26%	13%	24%
5	18%	4%	27%	11%	17%
6	30%	21%	37%	36%	25%

4.2. Negative Attributes

Brand	Insipid	Acid	Dry	Oxidative Color	Pasty
1	4%	12%	27%	21%	8%
2	7%	6%	12%	14%	9%
3	11%	9%	27%	15%	12%
4	22%	9%	31%	14%	17%
5	14%	11%	30%	20%	18%
6	6%	22%	13%	8%	12%

With CATA analysis, we can make a correspondence analysis, which is shown in Figure 7, explaining the deviation results obtained for all attributes within the analyzed products and which are presented in percentage (Fig. 7a). Five different positive attributes are presented: natural color, chipotle flavor, good firmness, juiciness and good odor, which represents 62% of the total of the attributes, which is higher than products four and five, and very similar to product 3. Product 2 and 6 are considered good products according to these attributes, which is in accordance with results previously discussed. We can observe that the prototype has a good chipotle taste, firmness and odor.

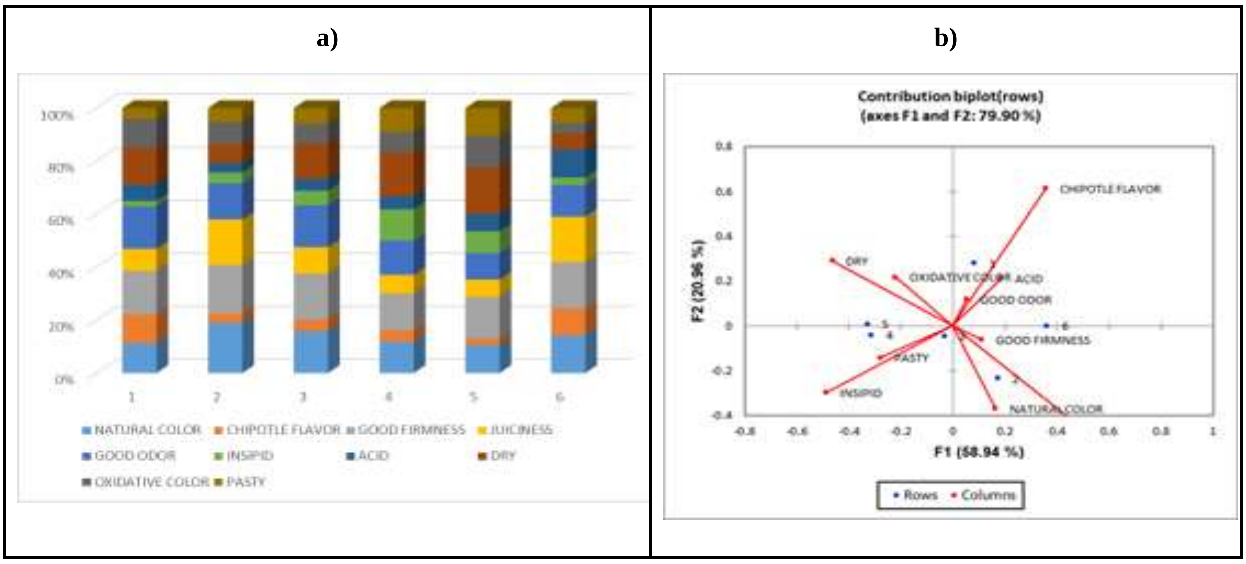


Figure 7. Correspondence Analysis carried out on the data from CATA questions with consumers, a) Percentage representation of the sensory attributes, b) Biplot representation of the samples and sensory attributes.

Furthermore, in Figure 7b the total inertia explained for the sensory attributes is based on two dimensions, which is 79.9%. This map allows us to visualize the relation between the attributes in the samples and the products that consumers may associate with them. In this sense, the product developed in our lab is associated with a high chipotle flavor, good odor and acidity.

In addition, the prototype is not considered pasty or insipid.

The Check all that apply (CATA) methodology can be used to characterize products, this type of experiments are based on asking if an attribute is present, and yes/no answers are obtained. CATA questionnaires are easily designed and can be easily answered (25). This binary option can be analyzed through different approaches. Its main feature is that it can establish differences among products by analyzing the products' attributes (61). Moreover, making this method excellent to combine attributes with the overall liking (OL), it generates a sensory profile of consumers, making it an extra tool in food development (62). This methodology used for the analysis of meat products is an easy and time saver procedure that can provide relevant information.

Finally, the decision tree is also a tool that gives the sensory marketing area a good idea of how to sell the products, because it can establish the acceptability of products according to the consumers grading and their socio-demographic differences. Figure 8 shows the analysis of the acceptability of product 1 according to consumers. It can be seen that product 1 is more liked by men (7.65 average grading) than women (6.75 average grading). In addition, the market segment of the developed prototype (Product 1) is young men (21.5) who ate out more than 5.5 times per week (8.13 average liking grade).

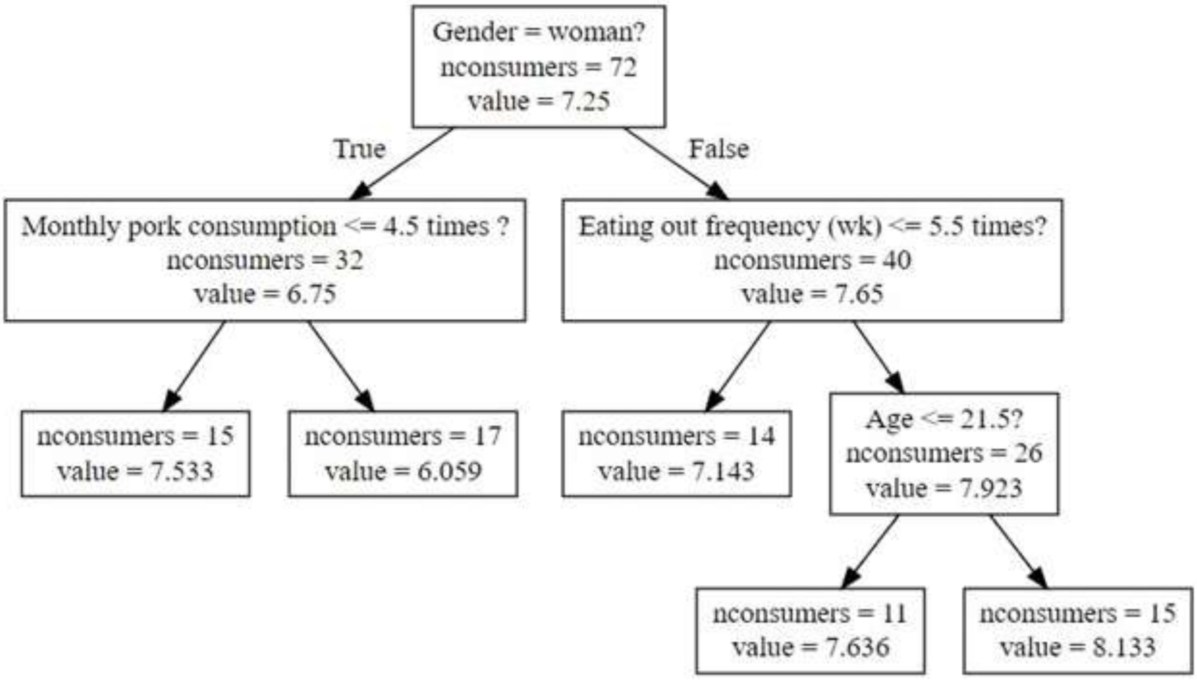


Figure 8. Decision tree of the prototype (Product 1) based on the sensory attributes.

Decision trees have been used for studying willingness to pay for different attributes of boneless pork loin in different places in Spain, where the consumers were more willing to buy according to visual pork fat; therefore, the marbled ones are preferred (63). This type of information is of importance for market purposes. Also, for classifying beer quality through chemical and sensory features that can be used as variables in decision tree techniques (63).

VI. Conclusions

In this research, we present a different approach in order to make a better decision for the first stages of launching a product into the market for a meat food product based in Data Science. Thus, this can provide complementary information, which can give us a better picture on how different products are accepted by consumers in different markets.

Regarding the prototype under evaluation, it can be concluded that the product developed in our lab, which is considered a prebiotic ready to eat pork product (Product 1), is a good product to scale up according to the sensory evaluation carried out in this study. On the one hand, it is a good source of nutrients; moreover, it can be functional due to the amount of inulin added (2.8%). On the other hand, it also showed a good acceptability related to all applied statistical sensory analysis: LSA, Landscape Product Liking, Hierarchical clustering, Gaussian Mixture Models, d' after JAR, CATA-frequency analysis and correspondence analysis and the Decision Tree. The integration of all the complementary analysis confirms that the prototype developed in our laboratory that can be described as a ready to eat prebiotic Sous Vide prototype could be scaled up and sold in Aguascalientes, México.

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