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Descriptive and hedonic sensory perception of Brazilian consumers for smoked bacon

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A R T I C L E I N F O

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A B S T R A C T

The descriptive and hedonic sensory perception of bacon manufactured using different smoking processes was studied. Six bacon samples were evaluated: three manufactured with woods, two with liquid smokes, and a commercial bacon. Consumers rated their overall liking (OL) and responded the check-all-that-apply (CATA) questions coupled with ideal profile method (IPM).[1] The preliminary result showed that LS2 and Bamboo were the best-rated bacons. However, data analysis indicated two segments of consumers (both n = 50), with significant differences in the OL. The first segment liked fatty and smoked bacons, while the second valued the texture and appearance. The drivers of liking in both segments were the attributes related to texture, juiciness and the smoky aroma. The use of different woods in the bacon smoking process modified the descriptive and hedonic sensory perception of consumers.

1. Introduction

Smoked bacon is consumed worldwide for its sensory characteristics, mainly developed during the processes of curing and smoking, which are highly appreciated by consumers (Saldaña et al., 2018c). Smoking is one of the oldest preservation techniques for meat and meat-based products (Toth, 1982). Initially, this technique was used to increase the shelf life of products from the pyrolysis of wood (Bortolomeazzi, Sebastianutto, Toniolo, & Pizzariello, 2007) and dehydration of the product (Fellows, 2009). Today, it is mainly applied to confer sensory properties, since it imparts desirable flavor and color to smoked foods (Suñen, Fernandez-Galian, & Aristimuño, 2001).

The wood used in the smoking process can influence the type and amount of compounds generated in the pyrolysis. It is known that hardwood varieties produce better smoke than softwoods, since the latter tend to produce higher concentrations of polycyclic aromatic hydrocarbons, in addition to having a greater amount of resins, which negatively affect the flavor of the product (Stumpe-Viksna, Bartkevičs, Kukare, & Morozovs, 2008). Despite these facts, there are few studies in the literature relating the type of wood or the use of liquid smokes with the sensory characteristics of smoked products (Malarut & Vangnai, 2018). Due to availability, cost, and because they are reforestation trees in Brazil, the Eucalyptus, Bambu, Acacia and Bracatinga woods are interesting options for use in traditional smoking and were chosen to be evaluated in this study (Saldaña et al., 2018c).

As it is widely known, the sensory properties of foods drive the consumer's liking (De Almeida, Villanueva, Pinto, Saldaña, & Contreras-Castillo, 2016; Selani et al., 2016), and consequently its success or failure in the competitive market (Giacalone, 2018). Descriptive analysis (DA) is one of the most flexible, powerful, sophisticated and widely used tools in sensory science (Murray, Delahunty, & Baxter, 2001), since it plays an important role to assist the meat scientist in describing the sensory profile of a product. However, DA has some limitations related to the high cost and time demanded to perform all the steps, from the panel screening to the final data analysis (Varela & Ares, 2012). Moreover, it is argued that the sensory profile obtained from DA does not necessarily represent the consumers' perceptions, and consumers are ultimately responsible for the success or failure of a product (Qannari, 2017). To overcome these limitations, in the last decade different sensory methods have been developed, tested, and

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[1] In the *ideal profile method*, the consumers indicate how they perceive real and ideal samples using a list of previously established attributes (Worch et al., 2013).

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optimized (Valentin, Chollet, Lelièvre, & Abdi, 2012). According to Delarue (2015), alternative sensory methods are fast and provide the sensory profile directly from consumers. Among these methods, free sorting task, projective mapping, and check-all-that-apply (CATA) questions have attracted the attention of the scientific community (Qannari, 2017).

The use of CATA questions has shown a fast growth because of its quick design and execution, and its simplicity to be performed (Ares, 2015). This method provides the sensory profile directly from consumers, and when coupled with overall liking (OL) and the description of the ideal product measures, it represents one of the most powerful tools for the development of foods (Saldaña et al., 2018b). Obtaining liking and sensory profile directly from consumers allows the segmentation of consumers based on their preferences (Varela, 2014). The internal preference mapping (MDPREF) and cluster analysis are appropriate techniques to explore the consumers segmentation, which have been widely used to relate the sensory profile and the OL of the different segments of consumers (Berget, 2018; Næs, Varela, & Berget, 2018).

The present study first explores the perception of all consumers through the CATA questions coupled with ideal profile method (IPM) and the OL. Then, the different OL patterns are studied, i.e., groups of consumers with similar preference within each group and different between groups. For this purpose, the members of each segment are identified by cluster analysis on the OL. Thus, in each cluster, the sensory attributes that modify the preference, also known as drivers of liking (DL), are determined by multivariate techniques.

In this context, the aim of this paper was twofold: to study the descriptive and hedonic sensory perception, as well as the DL of different smoked bacons using CATA questions coupled with IPM and OL of consumers; and to study the different OL patterns of consumer segments identified by cluster analysis.

2. Materials and methods

2.1. Samples

Bacons were manufactured using a complete block design, considering three different blocks (each block representing one independent processing). Pork bellies (70 kg, pH = 5.8, similar proportion fat/meat) were provided by the “Suinco” slaughterhouse (São Paulo, Brazil). Eucalyptus (*Eucalyptus citriodora*), Bamboo (*Bambusa vulgaris*) and Acacia (*Acacia mearnsii*) woods were used in the smoking process, in small pieces of $1 \times 1 \times 3\,cm^3$ and dehydrated at 240 °C for 30 min. Two commercial liquid smokes, consisting of natural condensates of smoke obtained by the pyrolysis of wood, was used: LS1 (pH = 2.50–4.50, density = 0.90–1.15 $g{\cdot}mL^{-1}$, Acidity = 10.00–11.00%, Salmonella in 25 mL: absence, Sodium = 2.40 $mg{\cdot}g^{-1}$), LS2 (pH = 2.20–2.20, density = 1.09–1.19 $g{\cdot}mL^{-1}$, Acidity = 9.50–11.00%, Salmonella in 25 mL = absence, Sodium = 1.50 $mg{\cdot}g^{-1}$). A commercial smoked bacon (composition in a portion of 10 g, according to the manufacturer: energy value = 46 kcal, dietary fiber = 0 g, carbohydrates = 0 g, saturated fat = 1.7 g, sodium = 77 mg, protein = 1 g, trans fat = 0 g, total fat = 4.7 g) was also included in the study.

The bacon processing was performed at the *Qualidade e Processamento de Carnes* Laboratory at the Department of *Agroindústria, Alimentos e Nutrição (LAN)* of the *Escola Superior de Agricultura “Luiz de Queiroz” (ESALQ) - Universidade de São Paulo (USP)*. Six types of bacon were evaluated in this study: three bacon samples were manufactured through conventional smoking, each one using a different wood from reforestation (Eucalyptus, Bamboo and Acacia); two bacon samples had the conventional smoking replaced by the use of two different brands of liquid smoke (called LS1 and LS2); and a commercial bacon sample that was added to the study for comparison purposes (Saldaña et al., 2018a).

For each independent processing, ten pork bellies were used, two for each of the five treatments prepared in the laboratory (Eucalyptus, Bamboo, Acacia, LS1 and LS2). The bacon manufacturing followed the recommendations of Saldaña et al. (2018c): 20% w/w of brine (3.0 g/100 mL NaCl, 0.6 g/100 mL sucrose, and 0.024 g/100 mL sodium nitrite) was injected over the whole belly. Subsequently, the belly was vacuum-packaged and stored at 4 °C for 24 h. Then, the belly was rinsed to remove excess salt from the surface and immediately placed in the smoker (Verinox, Italy), where an electrode was introduced into the product to monitor the temperature during the entire cooking process. The cooking process was carried out using a three-stage approach: first drying (65 °C for 30 min), then smoking (75 °C for 60 min) and, finally, steam cooking (at 75 °C for 30 min and then at 80 °C until the core temperature reached 75 °C). For the liquid smoking process, stage one (drying) and three (steam cooking) followed the same time-temperature program of the conventional smoking. However, in stage two (smoking), instead of receiving thermal treatment and smoke from the wood burning, the bellies were removed from the smoker and sprayed with liquid smoke in the proportion of 1% of the weight of the meat (selected based on pilot testing). After steam cooking, the samples of all treatments were cooled to room temperature, vacuum packaged, and subsequently stored at 2 °C for 24 h until sensory analysis.

2.2. Consumer sensory evaluation

The sensory evaluation was conducted in a single session of about 30 min, in the sensory analysis laboratory of the LAN/ESALQ/USP, equipped with individual booths and designed according to ISO 8589 (ISO, 2007). Before starting the test, consumers (in groups) underwent a training of approximately 10 min, using the same evaluation sheet of the analysis, in order to get to know the CATA questions coupled with IPM method. Bacon samples were sliced (0.3 × 4 cm) and cooked in a hot plate at 300 °C until the temperature of 75 °C was achieved. Sensory analysis was performed from the participants' prior scheduling. Due to this, the six samples of smoked bacon were cooked on time for each consumer. Once the samples were presented monadically, to maintain and standardize the temperature between the first and last sample, they were kept in an oven until they were offered to consumers. Bacon slices (50 g) were presented at 45 ± 2 °C in white plastic plates coded with three-digit random numbers, served monadically following a Williams Latin Square design (Wakeling & MacFie, 1995). Consumers evaluated the six samples, in a single session, with a stop of 10 min after the third sample, to avoid sensory fatigue. Mineral water was available for consumers to rinse the palate after each evaluation. Data collection was carried out entirely on A4 white paper.

2.2.1. Consumers

One hundred habitual consumers of bacon (60 women and 40 men, between 18 and 56 years old) were recruited among students and employees of the LAN/ESALQ/USP. The frequency of consumption of the consumer panel was: 28% declared to consume smoked bacon once a week, 27% three times a month, 22% once a month, 8% twice a week, 8% from time to time, 3% twice a month, and 4% presented a lower frequency of consumption. Before performing the sensory task, each consumer signed an informed consent form of voluntary participation.

2.2.2. Procedure

Consumers were accommodated in individual sensory booths, then the samples were presented, and they were asked to indicate their OL using a 9-point hedonic scale structured from “dislike extremely” to “like extremely”. Subsequently, they answered the CATA questions composed of 32 descriptors randomly presented. Consumers were asked to check all the descriptors that they considered appropriate to describe each sample. After evaluating all the samples, they were also asked to imagine an ideal bacon and describe it using the same descriptors list (Saldaña et al., 2018a, b; Worch, Lê, Punter, & Pagès, 2013).

The 32 descriptors (see Table 1) used in the questionnaire were the descriptive sensory attributes previously reported by Saldaña et al.

Table 1
Contingency table of the 6 bacon samples and the ideal bacon for the 32 CATA descriptors.

Descriptor	Samples						
	Ideal	Acacia	Bamboo	Eucalyptus	LS1	LS2	Commercial
Bright [ns]	42	43	44	38	38	36	54
Opaque [ns]	20	28	27	29	28	29	12
Little fatty***	59	12	27	19	11	41	24
Very fatty***	5	53	36	41	49	14	45
Appearance of red meat***	72	19	48	41	11	70	46
Homemade appearance [ns]	45	11	10	11	8	12	16
Appearance of white fat***	40	63	47	58	60	25	40
Appearance of yellow fat [ns]	20	24	29	23	28	30	36
Aroma that resembles a dinner***	39	18	23	15	8	20	38
Rancid aroma**	0	8	2	11	13	7	2
Homemade food aroma [ns]	54	24	12	25	14	28	23
Little artificial aroma [ns]	27	26	21	23	24	29	25
Artificial aroma*	2	9	23	18	26	14	16
Woody aroma*	41	19	30	20	9	16	21
Light smoky aroma***	48	58	28	53	50	58	34
Intense smoky aroma***	34	12	40	9	1	10	36
Little salty***	7	35	31	41	25	22	10
Very salty**	19	6	7	5	19	7	18
Light smoked taste**	27	50	35	49	56	44	30
Very smoked taste***	50	7	33	9	6	22	29
Little fatty taste***	61	14	34	18	12	39	26
Very fatty taste***	8	53	27	38	49	23	32
Little spicy*	32	37	31	45	46	37	26
Very spicy*	37	12	8	11	8	11	23
Soft [ns]	68	55	51	47	38	53	63
Hard*	0	11	11	21	16	7	8
Dry [ns]	19	6	14	13	8	9	7
Juicy***	74	44	34	25	23	54	48
Rubbery*	0	30	25	36	44	23	25
Fibrous [ns]	7	18	28	30	29	28	17
Little crispy [ns]	17	39	37	31	41	30	40
Very crispy [ns]	56	3	5	4	3	7	5

*** Indicates significant differences with $p < 0.001$.
** Indicates significant differences with $p < 0.01$.
* Indicates significant differences with $p < 0.05$, while [ns] indicates that there were no significant differences ($p > 0.05$) according to the Cochran's Q test. The ideal product was not used in the Cochran's Q test.

(2018c). Non-sensory terms were provided by an internal sensory evaluation team, composed by 10 experts in sensory evaluation of meat-based products, by means of the free description of the attributes that characterize the samples. Subsequently, the most cited attributes were maintained in the CATA questions.

2.3. Data analysis

First, the data analysis of the responses of the CATA questions and the OL of all consumers was carried out. Subsequently, consumers were segmented using Hierarchical Clustering on Principal Components (HCPC) on the OL scores. For each segment identified, the sensory profile and the OL were analyzed. Finally, the DL through Penalty Analysis (PA) and Partial Least Squares Regression (PLSR) models in each segment were obtained. Data analysis was performed in the R environment (R Core Team, 2017) using the SensoMineR (Le & Husson, 2008) and FactoMineR (Lê, Josse, & Husson, 2008) packages.

2.3.1. Overall liking

The OL of the six bacon samples was analyzed by the mixed ANOVA model, considering samples (fixed), consumers (random) and presentation order of the samples (fixed) as sources of variation at the level of 5% of significance. Tukey's means comparison test was performed to check for differences between the means.

2.3.2. Hierarchical clustering on principal components (HCPC)

A Principal Component Analysis (PCA) was carried out on the OL data considering the Pearson's correlation matrix. Samples and consumers were represented in the first two principal components to show the consumer's liking heterogeneity. This representation is also known as MDPREF (Macfie, 2007). The identification of the consumer members of each segment was proceeded using the first 5 eigenvectors of the MDPREF previously obtained (Argüelles, Benavides, & Fernández, 2014). These eigenvectors maintained 100% of the total inertia of the original data; therefore, the noise of the one hundred consumers was efficiently eliminated, making the segmentation process more robust. The hierarchical clustering was carried out on these 5 eigenvectors considering the Euclidian distance and the Ward's agglomeration method was employed to construct the dendrogram.

2.3.3. CATA questions

A contingency table was generated counting frequency of mention of each descriptor that characterized each target sample (Meyners, Castura, & Carr, 2013). Then, the non-parametric Cochran's Q test (Manoukian, 1986) was applied to identify significant differences between samples for each of the terms included in the CATA questions. The Cochran's Q statistic is shown for a target attribute in Eq.1.

$$Q = \frac{n_k(n_k - 1)\sum_{k=1}^{n_k}(T_k - \overline{T})^2}{n_k\sum_{j=1}^{nj}R_j - \sum_{j=1}^{nj}R_j^2} \quad (1)$$

Where k represents the samples, j represents the consumers, n_k represents the number of samples, n_j denotes the number of consumers, T_k expresses the total number of checks (1) of the attribute "a" for the sample "k", R_j expresses the total number of checks (1) of the attribute "a" for the consumer "j" in all the "k" samples, $\overline{T}$ expresses the total average of checks (1) of the attribute "a" for all the samples and is calculated by dividing the total number of checks by the number of samples. The Cochran's Q statistic was compared to a theoretical chi-square value with n(k-1) degrees of freedom.

The Correspondence Analysis (CA) was based on a contingency table composed of descriptors that showed significant differences between samples using the Cochran's Q test. The CA was also performed in each of the segments identified in the HCPC. It was constructed using the ϕ^2 index equivalent to the chi-squared statistics (Cariou & Qannari, 2018). The aim of this analysis is to obtain a perceptual map of samples, descriptors and the ideal bacon (supplementary individual). Around each bacon sample, confidence ellipses obtained by bootstrapping resampling were constructed with 500 virtual consumer panels (Cadoret & Husson, 2013). The confidence ellipses represented the multi-dimensional stability of each sample within the perceptual map, where two overlapped ellipses indicate similarity.

Finally, in each segment, a PA was applied in order to determine the mean drop of OL associated with the deviation of the ideal product for each descriptor included in the CATA question (Ares, Dauber, Fernández, Giménez, & Varela, 2014; Saldaña et al., 2018a). For each sample, the percentage of consumers who described the samples differently from the ideal bacon was calculated, as well as the change in the OL associated with the differences from the ideal characteristic. With the aim to analyze which attributes had the greatest impact on the OL, the mean drop of OL was plotted according to the percentage of consumers who described the sample evaluated as 'different from the ideal'. A threshold of 20% of consumers who found differences between the real and the ideal description was used (Popper, 2014). In addition, an arbitrary "mean drop of OL" threshold of 0.5 on a 9-point hedonic scale was used, aiming to pinpoint the attributes with a high mean drop of OL.

Furthermore, an analysis of dummy variables was carried out following the recommendations of Ares et al. (2014) and Saldaña et al. (2018a). Two dummy variables, coded as Z+ and $Z-$, were constructed, where Z is the target descriptor. A value of 1 was assigned to Z+ (presence of the attribute) and 0 to $Z-$ (absence of the attribute). When the descriptor was present in both the ideal and the target bacon, a value of 0 was assigned for Z+ and Z−. On these dummy variables, a Partial Least Squares Regression (PLSR) was performed to obtain the weight of deviation from the ideal product. For each sample and segment, an individual PLSR model was constructed considering the OL as a response variable and the dummy variables as independent variables. Finally, a summary table was elaborated with the dummy variables in the rows and the frequency of mention and the regression coefficient (RC) of each sample and segment in the columns. The intersection value of the PLSR model was considered as the maximum possible OL that a sample could obtain. The significant attributes for each PLSR model were identified as the most influential parameters in the mean drop of OL.

3. Results and discussion

3.1. Consumers segmentation

According to the results, LS2 (6.44) and Bamboo (6.42) were the most liked samples (ANOVA not shown for brevity). However, as it is widely known, the consumers' OL is segmented, therefore, the conclusions obtained from the average OL could hide the liking of some consumers who prefer other samples (Varela, 2014). In order to segment the consumers' preference into homogeneous groups, different multivariate analyzes were performed. Fig. 1A represents the OL of each consumer in the first two dimensions of the MDPREF, which maintained 56.57% of the total inertia of the original data. The consumer's OL was distributed, in its majority, in the second and third quadrant, while in the fourth and first quadrant the remaining consumers were positioned. The distribution of the samples in the MDPREF (Fig. 1B) followed the same behavior as the distribution of the consumers; Acacia and Eucalyptus were positioned in the second quadrant, while LS1 was located in the third quadrant. The remaining samples were distributed between the first and fourth quadrant.

After confirming that the consumer's OL is segmented, the allocation of the consumers in each segment was carried out. For this purpose, a HCPC was performed using a dendrogram height of 0.78 as the cut-off point (which is conservative, since the maximum value is 1), where two segments of 50 consumers were identified (Fig. 1C, D). To confirm significant differences ($p < 0.05$) between the segments and samples, a one-way ANOVA was performed, showing that the OL of segments was statistically different for Eucalyptus, Acacia, and Bamboo (Fig. 2). Therefore, the differences between the segments occurred in samples smoked with woods from reforestation, which have a particular and complex sensory profile originated from their volatile composition (Saldaña et al., 2018c). For segment 1, the best-rated samples were Eucalyptus, Acacia, LS2, and Commercial; for segment 2, the best-rated samples were Bamboo, LS2, and Commercial. To understand the reasons for the OL, the sensory characteristics of all consumers and of each segment were analyzed below.

3.2. Sensory characterization of the samples

Table 1 shows the frequency of mention of all consumers for the 32 descriptors that characterized the target samples and the ideal bacon. The Cochran's Q test identified 21 significant descriptors between samples ($p < 0.05$), which showed independence with the samples according to the Pearson's Chi-squared test (X^2: 812.78, *df*. 120, *p-value*: < 0.001), a necessary requirement for subsequent use of the CA. The CA is shown in Fig. 3 as a two-dimensional map (also called a perceptual map) that preserves 80.41% of the original inertia of data. In this perceptual map, bacon samples and the descriptors are represented. The ideal bacon was also projected as a supplementary individual. The distance between samples and attributes in the perceptual map is a measure of the association between them. In addition, the ellipses around samples represent their stability in the perceptual map; consequently, the overlapping of two confidence ellipses indicates multi-dimensional similarity between them.

Fig. 3 showed three groups of samples. The first group was located in the negative side of the first dimension and contained the following bacon samples: LS1, Acacia, and Eucalyptus (the confidence ellipses of the last two samples are overlapped). These bacon samples were characterized by their "appearance of white fat", "very fatty taste", "artificial aroma", "rubbery", "hard", "little salty", "little spicy", "light smoked taste", and "light smoked aroma". The second dimension separated the two remaining groups: on the positive side the Commercial and Bamboo samples were overlapped, being perceived by consumers as "very spicy", "with aroma that resembles a dinner", a "woody aroma", and a "very smoked taste". LS2 sample was located on the negative side of this dimension, which is characterized by "little fatty", "appearance of red meat" and "little fatty taste".

The ideal bacon is associated with bamboo and commercial samples, characterized by "very smoked taste" descriptor. However, because the OL of consumers is segmented, each segment was analyzed individually, to identify the different descriptors that characterize the ideal bacon in each segment. In this context, the following question arises: Is there an ideal product for each segment of consumers? The answer is "yes" (Worch & Ennis, 2013). To identify the ideal product of each consumer segment, as well as the position of the samples in the perceptual map, a contingency table was constructed for each segment and the samples associated with the statistically significant descriptors tested by the Cochran's Q test were subsequently plotted, with > 10% of frequency of mention.

Fig. 4 shows the perceptual map of segment 1, considering the first two dimensions of the CA based on the 20 significant attributes with a frequency of mention > 10%. In this segment, three groups of samples were found based on the overlapping of the confidence ellipses. The

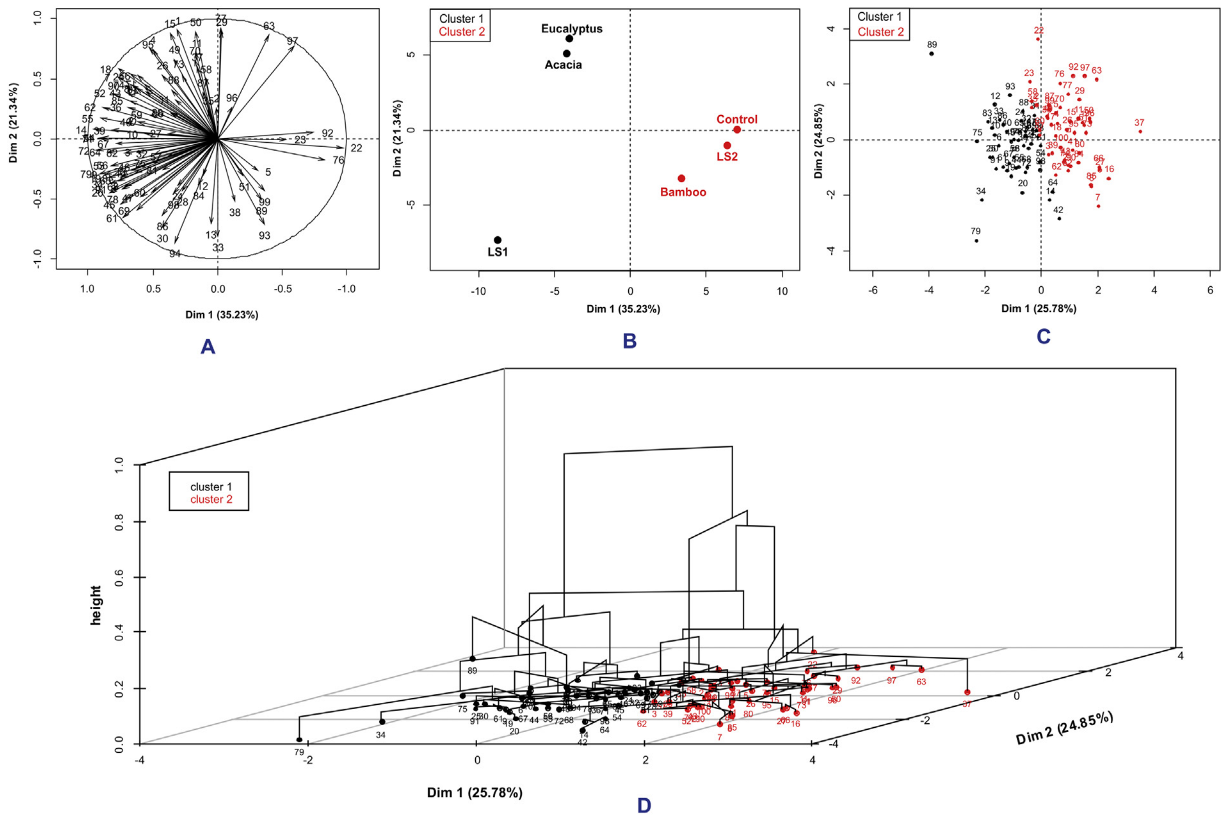

Fig. 1. Segmentation of consumers' panel. A: representation of the consumers in the MDPREF; B: Representation of the samples in the MDPREF, C: Factor map of consumers based on the two segments found; D: Representation of the consumers according to the cluster they belong to resulting from the HCPC. The overall liking was rated on a 9-point hedonic scale.

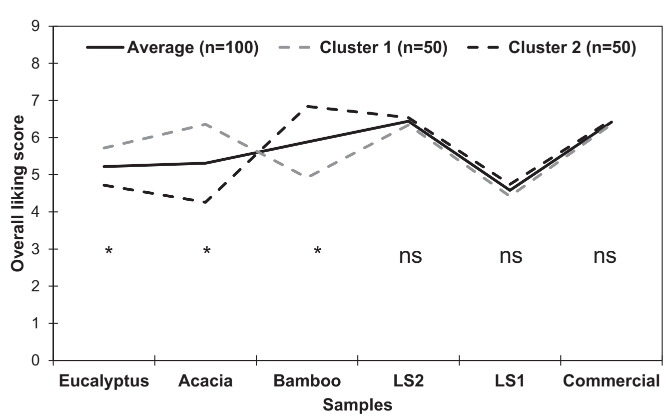

Fig. 2. Representation of the OL scores. LS1: Liquid smoked 1; LS2: Liquid smoked 2. Different letters indicate statistically significant difference between samples for each cluster according to the Tukey test at 5% of significance. The overall liking was rated on a 9-point hedonic scale.

first of them was positioned on the negative side of the first dimension (Acacia, LS1 and Eucalyptus) characterized by the attributes "very fatty", "very fatty taste", "artificial aroma", "appearance of white fat", "rubbery", "little spicy", "little smoked taste", "light smoky aroma" and "little salty", which were perceived as unpleasant. The second group included the Commercial sample that, unlike the perceptual map of all consumers, was not similar to the Bamboo smoked sample, being characterized by "very salty", "very spicy", "intense smoky aroma", and "homemade appearance".

The third group was positioned in the fourth quadrant of the perceptual map, composed of bacon smoked with Bamboo and LS2, which were perceived as "very smoked taste", "juicy", "soft", "woody aroma", "appearance of red meat", "little fatty taste" and "little fatty". These sensory attributes reveal that this segment valorizes few greasy products with smoked flavor. It is important to note that the position of the ideal sample in the first segment is similar to the data found when all consumers were considered (Fig. 3).

The perceptual map of the second segment of consumers in terms of samples, descriptors and ideal bacon is shown in Fig. 5. The ideal bacon was positioned on the negative side of the first dimension and was close to the LS2 sample, being perceived as "juicy", "appearance of red meat", and "little fatty". These descriptors indicate that the attributes related to the texture and appearance of bacon were the most valued by these consumers. Based on the results, the main difference between the two segments is that the first one appreciates the attributes associated with the smoking process, whereas the second segment shows the opposite behavior. Therefore, the first segment would be more susceptible to detect changes related to the smoking process. However, this information must be taken with care since the perception of sensory attributes is a multisensory phenomenon, i.e., the change of an attribute can modify the entire sensory profile.

3.3. Penalty analysis

In Fig. 6, the mean drop of OL (comparison between real and ideal sample) is displayed in both segments. The number of penalized attributes in the second segment was greater than in the first segment for most samples. Therefore, in the second segment, the ideal bacon was different from the samples studied. As mentioned above, the main difference between segments was the position of the ideal product and consequently the descriptors that the consumers expected to have in the ideal product. This variation in the sensory profile explains the differences in the number of penalized descriptors between segments. The segment 2 did not value sensory attributes related to the smoked taste.

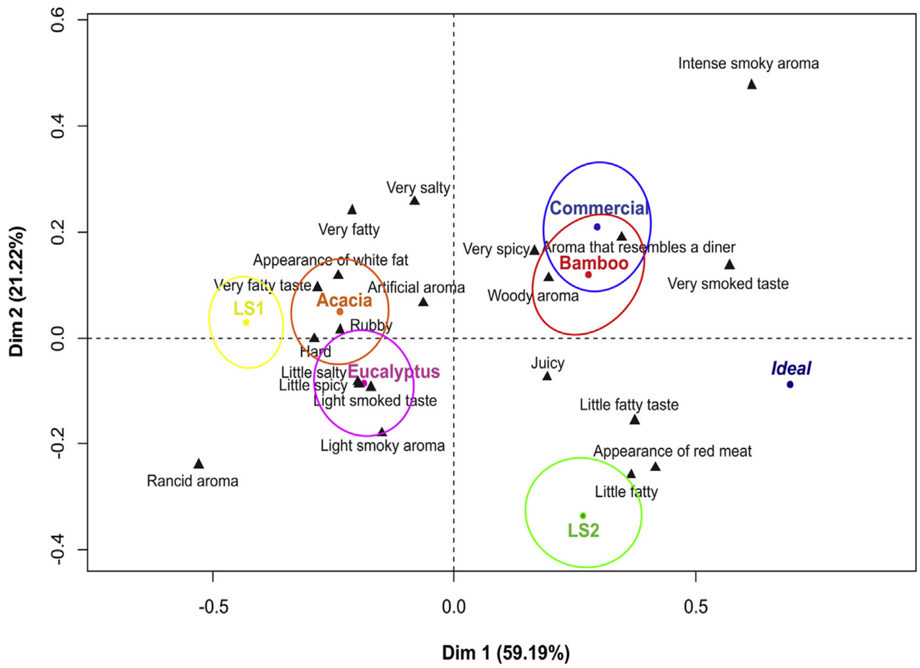

Fig. 3. Representation of samples and descriptors in the first two dimensions of CA of the CATA questions.

For this reason, the presence of sensory attributes related to the smoking process was penalized. For the Acacia sample, the first segment did not penalize any descriptor, while the second segment penalized 7 descriptors (“intense smoky aroma”, “rubbery”, etc.). For this reason, the first segment presented a higher OL score for Acacia bacon compared to the second segment. For the sample smoked with Bamboo, the first segment penalized 5 descriptors, while the second segment penalized 6. In the Commercial sample, the first segment penalized 3 descriptors related to appearance and texture while the second penalized 9 descriptors related to aroma, texture, and appearance. For bacon smoked with Eucalyptus, the first segment penalized 8 attributes and the second penalized 11 attributes, of which 5 attributes were penalized in common by both segments (“rubbery”, “very smoked taste”, “intense smoky aroma”, “juicy”, “very fatty”). Therefore, the remaining attributes caused the statistical difference in the overall liking between segments (Fig. 2A). The LS1 sample penalized 8 sensory attributes for the first segment and 11 sensory attributes for the second segment. However, this divergence in the number of attributes was not enough to impact on a significant difference in the OL score between the two segments. Finally, the LS2 sample presented 4 penalized attributes for the first segment, while the second segment penalized 9 attributes. It is important to note that, for both segments, LS2 sample was close to the ideal, but the segment 2 was more critical showing a more analytical behavior.

From the previous analysis, it is known that the penalization of descriptors varied from no penalized attribute to eleven penalized attributes, and these findings provide valuable information for consumers' perception and possible changes to be made in future reformulations to obtain an ideal product dedicated to specific consumer segments. To complement this analysis and, at the same time, to better select the descriptors that really drive the liking, the OL was modeled according to two dummy variables per sensory attribute for each segment and for each sample. For this purpose, each of the dummy variables was analyzed according to the significance of the RC and the percentage of citation. In this way, a significant positive (Z+) dummy variable indicates that consumers perceived it as absent in the target

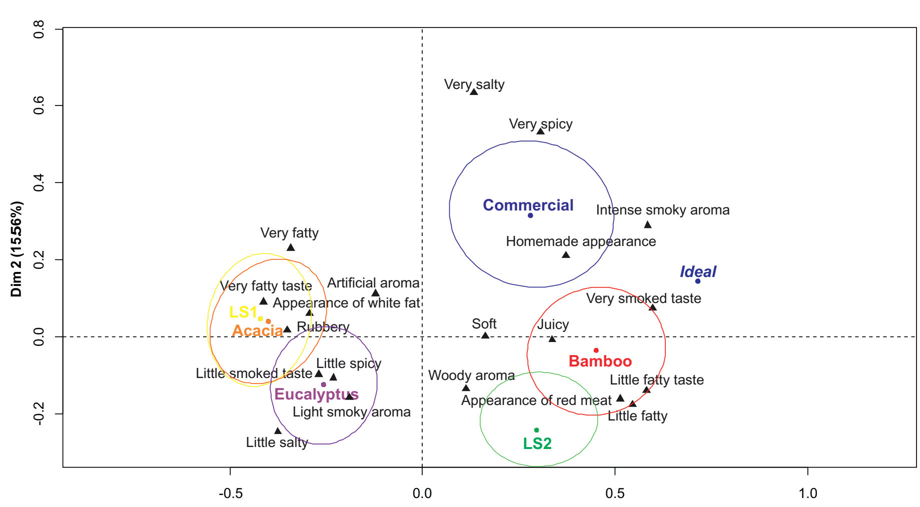

Fig. 4. Representation of the samples and descriptors characterized by the first segment (n = 50).

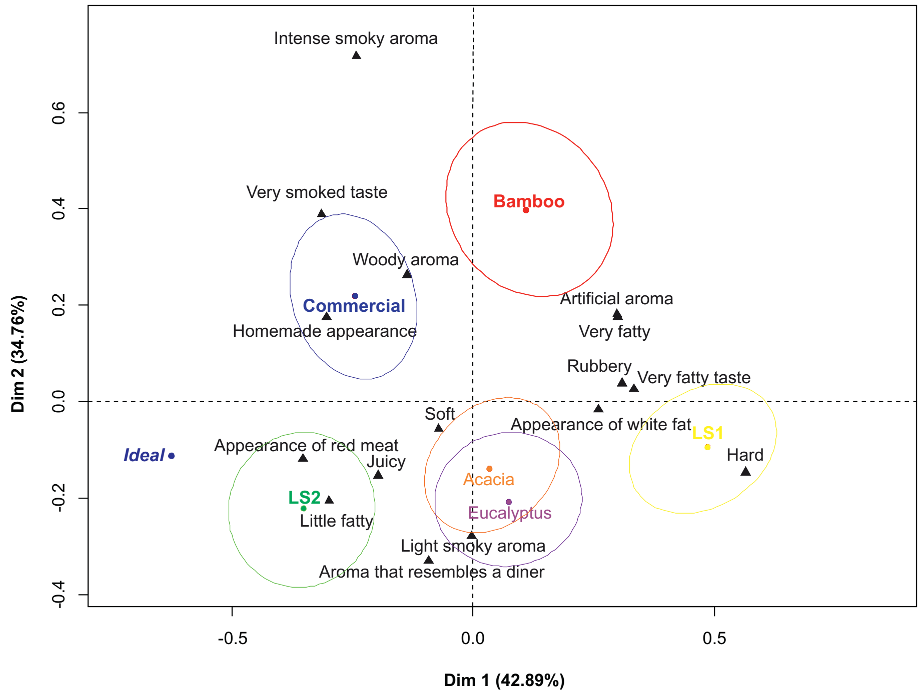

Fig. 5. Representation of the samples and descriptors characterized by the second cluster (n = 50).

bacon but desirable in the ideal bacon. Conversely, a significant negative ($Z-$) variable would indicate that consumers perceived in the target bacon a characteristic that they would not want in their ideal bacon.

According to Table 2, the mean "drop of OL" was affected by a reduced group of sensory attributes even lower than the number of attributes detected in the PA (Fig. 6). The dummy variable "rubbery-" was significant for most samples and segments. Therefore, this attribute is not regarded as a desirable characteristic of smoked bacon. "Juicy+" was the second most cited dummy variable and it presented significant regression coefficients. Thus, it is clear that the texture attributes can still be optimized. The texture of meat-based products depends mainly on the "meat-fat" ratio, which modifies the product's sensory profile, mainly in the Commercial sample. When analyzing the attributes related to the smoking process, the dummy variable "Intense smoky aroma+" stands out, i.e., consumers did not perceive this attribute in bacon smoked with Acacia in both segments, and in the LS2 bacon in the second segment.

The intercept of the models shows that, for the first segment, Bamboo, LS2, and Commercial bacons have potential to be highly accepted if the negative drivers of liking are optimized. In the second segment, the Commercial and LS2 samples showed the highest values for the intercept, thus it has the potential to obtain the maximum OL values. Both LS2 and the commercial bacon were the most preferred samples in the two consumer segments (Perrot et al., 2018).

3.4. Socio-demographic characteristics of the segments

The first segment of consumers preferred bacons smoked with Eucalyptus and Acacia, LS2, and the Commercial one. This segment of consumers liked fatty and smoked bacon (based on PA) and was composed of Brazilian female consumers (64%), with a high frequency of product consumption. On the other hand, the second segment preferred the Bamboo, LS2, and Commercial samples. This segment valued the attributes related to texture and appearance, which can be explained by the fact that the members had a low frequency of bacon consumption. In addition, this group had fewer women than the first segment (56%) and the nationality of the members was diverse, with a predominance of Brazilians (76%). The results obtained in the current study clearly show that the identification of homogeneous segments is extremely important in sensory analysis and consumer science (Westad, Hersleth, & Lea, 2004). Accordingly, the main reason for the different liking patterns in the segments were gender, frequency of consumption, and nationality. Based on the findings of Ares and Gámbaro (2007), age and gender are underlying factors that induce the food choice. It is important to mention that the reasons for the segmentation may be related to the context of consumption (Onwezen, 2018), genetic variation in taste and aroma (Sandell, Hoppu, & Laaksonen, 2018), and oral processing (Engelen, 2018), which cause differences in the rate of salivation, dental health, number of chewing, among other factors. These factors are beyond the scope of this study but they should be explored in future studies.

4. Conclusion

The preliminary conclusion based on the average liking indicated that the LS2 and Bamboo samples were statistically best rating than the other bacons. However, since the cluster analysis showed that the perception of the consumers was segmented, this hasty conclusion does not represent the reality of the consumer group.

Based on the results of each segment, the OL changed, since the best-rated samples for first segment were Eucalyptus, Acacia, LS2, and Commercial and for the second segment were Bamboo, LS2, and Commercial. According to the descriptors of the ideal bacon and the penalty analysis, the main differences between the two groups of consumers was related to the fact that, while segment one valorizes attributes related to the smoking, the second segment penalizes samples with these attributes.

LS2 and Commercial samples were the most preferred samples in the two consumer segments. The main drivers of liking in both segments were the attributes related to texture, as well as juiciness and the smoky aroma of bacon. Thus, in a further reformulation, these attributes should be optimized in the LS2 and Commercial samples, in order to produce greatly accepted bacons.

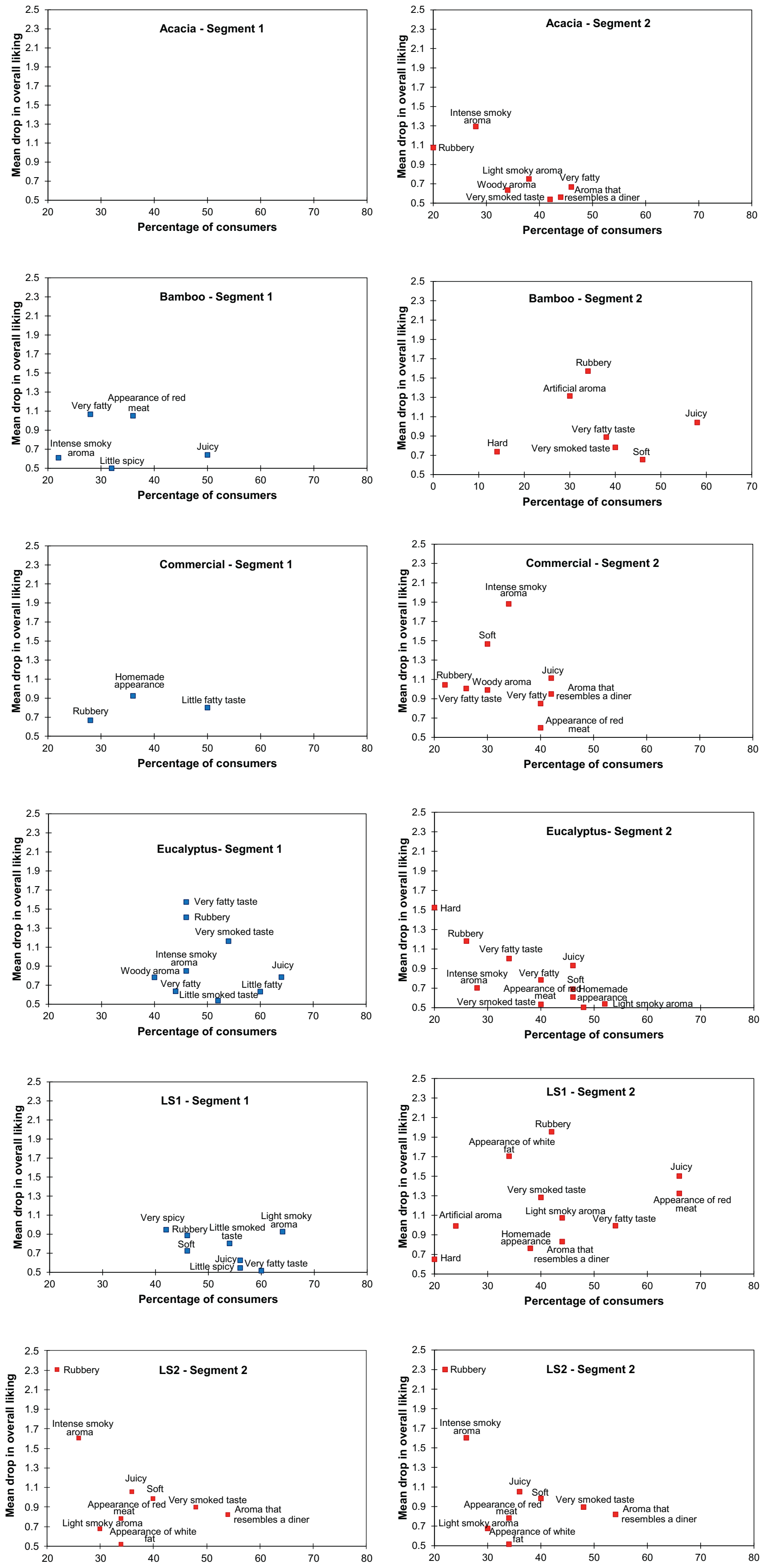

Fig. 6. Penalty analysis of each cluster considering the ideal bacon. The overall liking was rated on a 9-point hedonic scale.

Table 2
Regression coefficients and intercepts of the PLSR models used to study OL based on dummy variables. Significant coefficients are in bold with a gray background for easy reading.

Terms	Acacia				Bamboo				Eucalyptus				LS1				LS2				Commercial			
	Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2		Cluster 1		Cluster 2	
	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC	%	RC
Little fatty +	29	0.02	22	0.00	20	-0.24	25	0.06	26	**-0.38**	24	-0.12	25	0.17	26	-0.09	15	0.00	14	0.01	23	0.00	21	-0.13
Little fatty -	1	-0.61	3	0.31	9	0.37	4	0.37	4	0.37	6	0.06	0	0.00	3	0.77	5	-0.40	6	0.39	6	-0.35	3	0.14
Very fatty +	3	-0.30	2	0.31	3	0.46	1	1.27	1	0.58	2	0.84	1	-0.83	2	**1.22**	3	-0.63	1	1.12	2	0.25	1	-0.61
Very fatty -	32	0.03	21	-0.36	11	**-0.61**	24	-0.13	21	-0.33	18	**-0.51**	25	0.06	22	-0.28	9	**-0.52**	4	-0.49	24	-0.09	19	-0.33
Appearance of red meat +	31	0.08	27	-0.17	11	**-0.40**	22	-0.30	20	0.24	19	-0.37	32	-0.19	32	**-0.51**	8	0.12	9	-0.51	15	-0.05	18	-0.21
Appearance of red meat -	3	-0.47	2	0.31	7	-0.18	2	0.88	4	**-0.83**	4	0.26	2	0.13	1	0.22	7	0.18	8	0.02	5	-0.35	2	-0.39
Appearance of white fat +	4	0.25	4	0.07	8	0.23	6	-0.12	6	-0.45	5	-0.16	7	-0.09	4	-0.28	14	0.22	11	-0.18	10	0.31	7	-0.11
Appearance of white fat -	16	-0.01	15	-0.28	7	-0.12	14	0.09	12	0.16	17	-0.01	18	0.15	13	**-0.65**	4	-0.16	6	-0.16	7	-0.73	10	-0.20
Homemade appearance +	15	0.23	13	-0.08	8	0.07	17	-0.38	14	0.22	19	-0.37	16	0.01	19	-0.29	13	0.25	17	-0.18	9	-0.02	8	0.20
Homemade appearance -	3	0.54	4	0.07	4	-0.04	5	0.49	4	-0.35	5	0.34	4	0.13	0	0.00	6	-0.49	5	0.12	9	-0.66	7	-0.11
Artificial aroma +	1	0.36	0	0.00	0	0.00	1	-1.21	1	-1.23	1	-1.72	1	0.60	0	0.00	1	1.24	0	0.00	1	-0.71	0	0.00
Artificial aroma -	5	-0.56	3	0.31	8	-0.37	14	-0.44	14	0.08	4	-0.11	13	-0.13	12	-0.38	5	0.14	8	-0.23	11	0.04	4	-0.77
Woody aroma +	13	-0.22	15	-0.41	7	0.07	14	0.21	14	0.08	16	0.06	17	-0.02	19	0.07	11	0.23	16	-0.13	14	0.01	11	-0.36
Woody aroma -	4	-0.01	2	0.55	4	-0.34	6	0.27	6	**-0.95**	3	0.30	3	-0.70	1	-0.16	0	0.00	2	0.71	1	-0.23	4	-0.41
Light smoky aroma +	10	-0.33	8	-0.27	10	-0.20	20	-0.01	11	-0.25	13	-0.06	12	-0.20	14	-0.33	10	-0.02	7	-0.09	17	**-0.47**	14	-0.31
Light smoky aroma -	17	**0.45**	11	-0.27	6	0.42	4	-0.29	16	0.06	13	-0.25	20	-0.27	8	-0.25	19	0.07	8	-0.35	11	**0.42**	6	0.15
Intense smoky aroma +	17	**0.32**	10	**-0.49**	7	-0.05	5	-0.50	20	-0.35	11	-0.47	22	-0.16	12	-0.29	18	-0.12	10	**-0.74**	14	0.15	4	-0.88
Intense smoky aroma -	1	-1.58	4	**-0.56**	4	-0.44	14	0.17	3	-0.18	3	0.30	0	0.00	1	1.39	1	-0.27	3	-0.15	7	-0.18	13	**-0.62**
Little salty +	2	0.61	-	-	2	0.25	-	-	0	0.00	-	-	2	0.62	-	-	4	0.78	-	-	3	0.76	-	-
Little salty -	22	-0.26	-	-	11	-0.01	-	-	27	-0.12	-	-	11	-0.12	-	-	11	**-0.51**	-	-	3	0.26	-	-
Very salty +	13	-0.17	-	-	13	-0.04	-	-	14	0.04	-	-	13	0.41	-	-	13	-0.05	-	-	9	0.23	-	-
Very salty -	1	0.36	-	-	3	0.19	-	-	0	0.00	-	-	6	-0.31	-	-	1	0.73	-	-	4	0.27	-	-
Little smoked taste +	6	-0.41	-	-	5	-0.26	-	-	4	-0.23	-	-	2	0.37	-	-	3	0.42	-	-	7	-0.42	-	-
Little smoked taste -	21	0.14	-	-	11	0.03	-	-	22	-0.17	-	-	25	-0.43	-	-	16	-0.16	-	-	12	0.17	-	-
Very smoked taste +	25	-0.06	20	-0.31	12	-0.12	14	-0.24	25	-0.39	19	-0.22	27	-0.15	19	**-0.45**	20	0.05	17	-0.36	21	0.00	11	-0.10
Very smoked taste -	1	-0.61	1	0.77	3	-0.07	6	-0.27	2	-0.79	1	-0.33	1	-0.35	1	-0.55	2	0.24	7	-0.09	6	0.01	5	0.12
Little fatty taste +	29	0.06	-	-	17	-0.17	-	-	23	-0.02	-	-	26	0.03	-	-	16	-0.12	-	-	20	-0.30	-	-
Little fatty taste -	1	-0.61	-	-	12	0.12	-	-	0	0.00	-	-	1	0.60	-	-	8	0.12	-	-	5	-0.25	-	-
Very fatty taste +	2	0.86	3	-0.01	4	**0.57**	1	-1.62	3	-0.34	2	-0.58	5	-0.18	3	0.64	3	0.07	1	-0.56	4	0.52	1	-0.61
Very fatty taste -	29	-0.29	21	-0.02	6	**-0.56**	18	-0.23	20	-0.64	15	-0.38	25	-0.17	24	**-0.52**	12	-0.40	7	-0.51	17	-0.38	12	**-0.40**
Little spicy +	8	-0.22	-	-	8	-0.04	-	-	9	-0.03	-	-	8	-0.20	-	-	8	0.05	-	-	9	-0.21	-	-
Little spicy -	12	0.41	-	-	8	-0.26	-	-	17	-0.05	-	-	20	-0.15	-	-	11	0.00	-	-	5	0.27	-	-
Very spicy +	18	0.01	-	-	14	0.01	-	-	16	-0.10	-	-	19	-0.24	-	-	18	-0.03	-	-	12	-0.04	-	-
Very spicy -	3	0.21	-	-	1	-0.32	-	-	2	-0.56	-	-	2	-1.34	-	-	2	-0.53	-	-	7	**0.05**	-	-
Soft +	18	-0.23	10	-0.32	11	-0.23	19	-0.33	22	-0.32	15	-0.38	19	**-0.56**	21	0.04	14	-0.86	15	**-0.52**	11	0.09	7	**-0.84**
Soft -	5	0.29	10	0.20	9	0.12	4	0.15	8	0.21	8	0.02	4	0.64	6	-0.40	9	0.14	5	0.12	5	-0.35	8	-0.25
Juicy +	27	-0.12	12	-0.17	19	-0.37	28	**-0.42**	30	-0.28	22	-0.40	26	-0.20	30	**-0.62**	14	-0.61	15	**-0.55**	19	**-0.24**	17	**-0.63**
Juicy -	5	0.07	4	0.32	6	0.28	1	0.03	2	-0.33	1	-0.33	2	-0.61	3	0.37	6	0.16	3	0.29	6	0.01	4	0.30
Rubbery +	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00
Rubbery -	20	0.03	10	**-0.49**	8	-0.20	17	**-0.64**	23	**-0.63**	13	-0.53	23	-0.42	21	**-0.74**	12	-0.62	11	**-0.95**	14	**-0.31**	11	**-0.46**
Aroma that resembles a diner +	-	-	19	-0.23	-	-	25	-0.03	-	-	17	-0.05	-	-	20	-0.27	-	-	20	-0.54	-	-	18	-0.21
Aroma that resembles a diner -	-	-	3	-0.18	-	-	1	0.45	-	-	7	0.07	-	-	2	-0.36	-	-	7	0.39	-	-	3	-0.94
Hard +	-	-	0	0.00	-	-	0	0.00	-	-	0	0.00	-	-	0	0.00	-	-	0	0.00	-	-	0	0.00
Hard -	-	-	4	-0.31	-	-	7	-0.30	-	-	10	**-0.69**	-	-	10	-0.25	-	-	3	-0.44	-	-	1	-0.61
Intercept	4.35		7.36		7.48		5.98		6.56		7.14		6.02		6.62		7.25		7.69		7.16		7.85	
Mean overall liking	6.36		4.26		4.92		6.84		5.72		4.72		4.42		4.74		6.34		6.54		6.36		6.48	
Mean drop *	2.01		3.10		2.56		0.86		0.84		2.42		1.60		1.88		0.91		1.15		0.8		1.37	

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