Can consumer segmentation in projective mapping contribute to a better understanding of consumer perception?

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Abstract

In projective mapping tasks assessors create an overall representation of the similarities and differences among samples by relying on a process of synthesis for analyzing and processing sensory information. Individual differences in consumers' information processing and preference patterns could strongly affect which sensory characteristics they consider more relevant for estimating similarities and differences among samples. Therefore, low-dimensional consensus configurations (obtained via MFA or GPA) may not represent the perception of some consumer segments. This could lead to inaccurate conclusions about consumers' sensory perception of the products or at least to the loss of valuable information about the perception of some consumer groups. In this context, the aims of the present work were to explore consumer segmentation in projective mapping. Datasets from nine studies with 81-102 consumers were analyzed to explore consumers' segmentation. Through applying hierarchical cluster analysis on consumers' coordinates in the first four dimensions of the MFA, between 2 and 4 groups of consumers were identified in each study. Sample configurations and consumers' descriptions strongly differed among the groups, indicating heterogeneity in the relative relevance they gave to the sensory characteristics of the samples for estimating the similarities and differences among samples. In all cases it was observed that the consensus configuration was highly similar to the configuration of one of the groups, which was not necessarily the larger but the one with the highest explained variance by the first dimension of the MFA. These results suggest the need to explore segmentation when analyzing data from projective mapping tasks, and to further study the relationship between consumers' holistic perception of products and preference patterns.

Keywords: *sensory characterization; consumer profiling; consumer research; MFA; napping*

Research highlights

- Data from 9 projective mapping studies were used to explore consumer segmentation
- Hierarchical cluster analysis was performed on consumers' coordinates of the MFA
- Between 2 and 4 groups of consumers were identified in each study
- Sample configurations and consumers' descriptions strongly differed among the groups
- Consumer segmentation in projective mapping tasks deserves further exploration

1. Introduction

Interest in consumer-based methodologies for sensory product characterization has steadily grown in the last decade, partly motivated by the need to directly include consumer input in the new product development process (Valentin, Chollet, Lelièvre, & Abdi, 2012; Varela & Ares, 2012). Research showing that consumers can provide accurate information about the sensory characteristics of products (Husson, Le Dien, & Pagès, 2001; Moskowitz, 1996; Worch, Lê, & Punter, 2010; Ares, Bruzzone & Giménez, 2011) has led to the development of new consumer-based methodologies (Varela & Ares, 2014).

Holistic methodologies are among the most popular novel methodologies for sensory characterization which are being increasingly used for uncovering consumers' perception of food products (Varela & Ares, 2012). These methodologies are based on the evaluation of global similarities and differences among samples, and therefore they are useful to identify the main sensory characteristics underlying judgments of perceived similarity (Ares & Varela, 2014). Projective mapping is one of the most popular holistic methods. Assessors are asked to position samples on a bi-dimensional space according to their global similarities and differences (Risvik, McEwan, Colwill, Rogers, & Lyon, 1994), being able to simultaneously consider more than one sensory characteristic. Projective mapping has already been applied for sensory characterization of a wide range of food product categories, including chocolate, cheese, wine, citrus juices, fish nuggets, milk desserts, crackers, and fruits (Albert, Varela, Salvador, Hough, & Fiszman, 2011; Bárcenas, Pérez-Elortondo, & Albisu, 2004; Hopfer & Heymann, 2013; Nestrud & Lawless, 2008; Pagés, 2005; Risvik et al., 1994; Vidal, Cadena, Antúnez, Giménez, Varela & Ares, 2014).

In a projective mapping task assessors should form an overall representation of the similarities and differences among samples by relying on a process of synthesis for analyzing and processing sensory information (Jaeger, Wakeling, & MacFie, 2000). This process of synthesis determines the relative importance of the perceived sensory characteristics for estimating the similarities and differences among samples. For this reason, individual differences in the criteria used by assessors to evaluate samples and complete the task are expected. These individual differences are worth studying, particularly when working with naïve consumers (Nestrud & Lawless, 2008).

Heterogeneity in how consumers perceive food products has been long recognized, i.e. consumers have been reported to differ in how they perceive products (e.g., Prutkin et al., 1972) and/or in the relative importance they attach to the sensory characteristics of products (Carroll, 1972; Love, 1994; Harwood, Ziegler, & Hayes, 2012; Moskowitz & Krieger, 2000). Considering that projective mapping tasks do not involve training in attribute recognition or quantification (Valentin et al., 2012), and also that consumers are not specifically asked about individual attributes but rather to assess them holistically, consumers can generate different sensory spaces which reflects differences in how they perceive samples and how they cognitively assess them. Individual differences in consumers' information processing and cognitive structure and task-related factors can affect synthesis processes and, consequently, the number of sensory characteristics that are simultaneously considered for estimating similarities and differences among samples (Malhotra, Pinson, & Jain, 2010). For these reasons, sample spaces are expected to strongly differ among assessors.

Generalized Procrustes Analysis (GPA) or Multiple Factor Analysis (MFA) are used to handle heterogeneity in individual maps and to obtain a consensus sample configuration in a low-dimensional space (Dehlholm, 2014). However, the low-dimensionality of this sample configuration may not reflect the cognitive representation of all consumers (Summers & MacKay, 1976). Therefore, the perception of consumer segments may be underrepresented in consensus configurations from projective mapping, which could lead to inaccurate conclusions about consumers' sensory perception of the products.

In this context, the aims of the present work were to explore the occurrence of consumer segmentation in projective mapping tasks and to estimate its effects when analyzing data from consumer-based sensory characterization studies using this methodology.

2. Materials and methods

Data sets from nine different consumer studies with different product categories (Cadena et al. 2014; Vidal et al., 2014b) were re-analyzed to explore consumers' segmentation. Table 1 shows the description of the data sets.

2.1. Consumers

Between 81 and 102 consumers participated in the studies (Table 1). In each study consumers were recruited based on their consumption of the target product, as well as their interest and availability to participate in the study. Participants were aged 18–75 years old and the percentage of females ranged from 51% to 73%. Consumer samples were not representative of the general population of the cities in which the studies were performed (Montevideo -Uruguay- and Gualeguaychú –Argentina-).

2.2. Samples

Four product categories were considered: crackers, milk desserts, orange-flavoured powdered drinks, and yogurt. Samples in Studies 1, 2, 7 and 8 corresponded to commercial brands available in the market, which were purchased from local supermarkets. In Studies 3 - 6 vanilla milk desserts were prepared using water, powdered skimmed milk, inulin, modified maize starch, commercial sugar, polydextrose, sodium tripolyphosphate, carrageenan, vanilla aroma, caramel aroma, egg yellow food colouring and sucralose (Vidal et al. 2014b). In Study 9 yogurts were formulated with skimmed pasteurized milk, commercial sugar, skim milk powder, modified starch, locust bean gum, pectin, and lyophilised cultures of *S. thermophilus, Lactobacillus bulgaricus, Lactobacillus acidophilus,* and *Bifidobacteriumlactis* (Cadena et al. 2014).

Six or eight samples were included in the studies, as shown in Table 1. Samples were presented to consumers in plastic containers labelled with three-digit random numbers, and were served all at once in random order for their comparison. Mineral water was available for rinsing between samples but it was not enforced.

2.3. Data collection

The studies took place in standard sensory booths, under white lighting, controlled temperature (22-24ºC) and airflow conditions. Explanation on how to perform the test was provided to participants at the beginning of each study. Consumers were asked to evaluate the samples and to place them on an A3 white sheet (42cm x 30cm), according to their similarities and differences, in a way that two samples perceived as similar should be located close together on the sheet, whereas samples perceived as very different had to be placed far from each other. They were asked to complete the task using their own criteria and they were told that there were no right or wrong answers. After completing the projective mapping task, consumers were asked to provide a description of the sensory characteristics of each of the samples.

2.4. Data analysis

The X and Y coordinates of the samples on each consumer's individual map were determined by measuring their position on the A3 sheet, considering the left bottom corner as the origin of the coordinate system. A Multiple Factor Analysis (MFA) was performed on the coordinate data, considering the data from each consumer as a separate group of variables (Pagès, 2005). Sample configurations obtained through this analysis for each study are called "consensus”. Confidence ellipses were constructed using parametric bootstrapping (Dehlholm, Brockhoff, & Bredie, 2012).

Consumers' representation in the relationship square of the MFA (i.e. the representation of the groups of variables) provides a measure of the similarity between their individual sample configurations (Pagès & Husson, 2014). In this representation, the coordinates of each consumer (group of variables) on the MFA dimensions correspond to the *Lg* measure between the X and Y coordinates of each individual sample map (the variables of each group) and each of the MFA dimensions. The *Lg* measure is an indicator of the relationship between a group of variables and a dimension. The proximity of two consumers (groups) in this representation is a consequence of the similarity in the structures they induce on the samples (Lê, 2014). Groups of consumers with similar individual maps were identified using hierarchical cluster analysis on consumers' coordinates in the first four dimensions of the MFA. Four dimensions were kept in the analysis as for 8 of the 9 studies considered the percentage of variance explained by the first two dimensions of the MFA was lower than 70% (Table 2), while for all studies at least 70% of explained variance was explained by the first four dimensions (data not shown). Euclidean distances and Ward's clustering method were used in the clustering procedure, and the optimum number of clusters for each study was determined based on the Calinski and Harabasz index (Milligan & Cooper, 1985).

Projective mapping data were analyzed separately for each of the consumer groups identified in hierarchical cluster analysis following the same procedure than for the original datasets. However, to interpret the results of each consumer group, only the first two dimensions of the MFA were considered, regardless of the cumulative percentage of explained variance by the second dimension. Considering that the majority of the participants in projective mapping studies pay attention to one or two dimensions, even if the sample set has multiple sources of variation (Nestrud & Lawless, 2011), it seemed reasonable to assume that the consensus sample space within a cluster would be two-dimensional.

Similarity between the sensory spaces provided by the identified consumer groups was evaluated using the RV coefficient (Robert & Escoufier, 1976) between sample configurations in the first two dimensions of the MFA. The RV coefficient was also used to evaluate the similarity between the sample configuration of each of the consumer groups identified and the consensus configuration of each study. RV coefficients between the first two dimensions of the MFA of each cluster and all the possible pairs dimensions from the first four dimensions of the consensus configuration (i.e.,1 and 2, 1 and 3, 1 and 4, 2 and 3, 2 and 4, 3 and 4) were calculated. The significance of the RV coefficient was tested using a permutation test (Josse, Pagès, & Husson, 2008).

All the words provided by participants in the description phase were qualitatively analysed. The terms elicited to describe each sample or group of samples were grouped by consensus between two researchers. Terms mentioned by at least 5% of the consumers were retained for further analysis. Global chi-square analysis was used to evaluate differences in the frequency of mention of the terms among consumer groups. When the global chi-square test was significant, a chi-square per cell analysis was performed to identify its source of variation (Symoneaux, Galmarini, & Mehinagic, 2012). The chi-square per cell test determines if the observed values of each cell of a contingency table are significantly higher, lower of equal to the expected ones (Symoneaux & Galmarini, 2014).

The frequency table containing terms generated by each group of consumers and their frequency of mention was considered a set of supplementary variables in the MFA of projective mapping data.

All statistical analyses were performed with R language (R Core Team, 2013). FactoMineR was used to perform MFA and to compute the RV coefficient (Lê, Josse, &Husson, 2008), and NbClust was used to determine the optimum number of clusters for each study (Charrad, Ghazzali, Boiteau & Niknafs, 2013).

3. Results

3.1. Hierarchical cluster analysis

Results from hierarchical cluster analysis and MFA are summarized in Table 2. In the nine consumer studies between 2 and 4 groups of consumers (referred to as clusters from now on) were identified, with relative sizes ranging from 12.4% to 58.2% (Table 2).

The RV coefficients between sample configurations of each of the identified clusters and the consensus configurations ranged from 0.073 ($p=0.928$) and 0.975 ($p=0.005$) when the first two dimensions of the MFA were considered. The majority of the clusters' sample configurations (70.5%) were significantly correlated to the consensus configurations when the first two dimensions of the MFA were considered. However, in 6 out of 9 studies there was at least one cluster with a sample configuration that was not significantly correlated to the consensus sample configuration in the first two dimensions of the MFA. The highest correlations between clusters' and consensus configurations in the first two dimensions were found for the clusters that had the highest explained variance by the first two dimensions of the MFA, which were not necessarily the largest clusters. In fact, in studies 2, 6, 7 and 8 the clusters with the highest RV with the consensus configurations were not the ones with the largest relative size. For the rest of the clusters, their correlation with the consensus configuration depended on both the percentage of variance explained by the first dimension and their relative size (Table 2).

For some of the clusters, sample configurations in the first two dimensions of the MFA were more correlated to higher dimensions of the consensus configuration than to the first two dimensions (Table 2). For example, in Study 1 the first two dimensions of the configuration of cluster 1 were more correlated to dimensions 2 and 3 of the consensus configuration than to the first two dimensions. When the highest RV coefficients between the first two dimensions of the clusters' MFA and two of the first four dimensions of the consensus MFA were considered, values ranged from 0.531 (p=0.048) to 0.975 (p=0.005) (Table 2). All the RV coefficients were significant, except for the configuration of one cluster in Study 7 that was almost significant (p=0.058). This result suggested that each cluster was related to a part of the consensus configuration, which indicated that the clusters gave different relative importance to the sensory characteristics of samples when evaluating their similarities and differences.

The similarity of sample configurations among the identified clusters for each study was assessed by computing the RV coefficient in the first two dimensions of the MFA. The RV coefficients ranged from 0.022 to 0.776, while the p-values varied between 0.0109 and 0.9649 but only 16.7% of them were significant.

3.2. Description of sample configurations for the identified consumer clusters

Similarities and differences between sample configurations in the first two dimensions of the MFA for the consensus and the different clusters identified in each study were analyzed. In the majority of the studies there was at least one cluster with a sample configuration very different to the consensus, and at least one cluster with a sample configuration similar to the consensus. However, consumer segmentation of projective mapping data led to different results depending on the study. Examples are discussed below.

The three consumer clusters identified in Study 4 had sample configurations with clearly different correlation to the consensus sample configuration (Table 2). In the first two dimensions of the MFA, sample configuration of Cluster 2 (relative size 52%) was extremely similar to the consensus (Figure 1 (a) and (d)), which is in agreement with the high RV coefficient obtained (RV=0.958). Sample grouping in the sample configuration of Cluster 1 (relative size 30%) was somehow similar to the consensus, with the exception of samples B6 and B8 that were placed together in a distinct place in the consensus sample configuration, but were overlapped with sample B5 in sample configuration from Cluster 1 (Figure 1(c)). The separation of samples in the first dimension of the MFA for Cluster 1 corresponded to the second dimension of the consensus configuration, suggesting that Clusters 1 and 2 might be categorizing samples differently weighting some product characteristics. The RV between these two configurations reflected that fact, it was significant but not so high (RV=0.759). On the other hand, sample configuration of Cluster 3 (relative size 18%) was not significantly correlated to consensus configuration. Consumers in this cluster placed samples B1, B2, B5 and B6 at positive values of dimension 1, and samples B3, B4, B7 and B8 at negative values (Figure 1(e)). Interestingly, this distinction in two groups corresponded to samples with different flavour. The first group of samples (B1, B2, B5 and B6) were formulated with vanilla aroma, while the others were prepared with caramel aroma. In the consensus configuration (Figure 1 (a)), sample grouping in the first two dimensions can be explained by two characteristics: texture and sweetness. Samples formulated without sucralose (B1, B3, B5 and B7) were placed at negative values of the first dimension of the MFA, while samples with sucralose were located at positive values. On the other hand, samples placed at negative values of the second dimension of the MFA (B1, B2, B3 and B4) were formulated to have a runny texture, whereas samples B5, B6, B7 and B8 were thicker. Apparently, the type of aroma did not play a role in sample discrimination of the consensus in the first two dimensions of the MFA, nor in the first four dimensions of the MFA of Clusters 1 and 2.

However, in the third and fourth dimensions of the consensus sample configuration, it can be observed that samples with caramel aroma were placed at positive values of the third dimension, while samples formulated with vanilla aroma were placed at negative values. This explains the fact that the highest RV coefficient between sample configuration of Cluster 3 in the first two dimensions was found with the third and fourth dimension of the consensus (Table 2). In this study higher dimensions should be considered in order to represent consumer perception of all clusters. These results clearly show the existence of groups of consumers who weighted sensory modalities or individual attributes differently for the categorization or else that the differences in threshold of detection of certain aromas or tastes could play a role in the categorization.

Study 5 provided similar insights on the differences between the clusters' and the consensus configuration. Sample configuration in the first two dimensions of the MFA of Cluster 2 was clearly different from the consensus sample configuration in the first to dimensions (Figure 2 (a) and (d)), which is in agreement with the fact that the RV between these configurations was not significant. However, sample configuration of Cluster 2 was highly similar to the consensus configuration in the third and fourth dimensions of the MFA (Figure 2(b) and (d), Table 2). Meanwhile, sample configuration from Cluster 1 (relative size 46%, Figure 4 (c)) was significantly correlated to the consensus (RV = 0.896). In both sample configurations two groups were located in opposite sides of the first dimension: samples C1, C3, C5 and C7 opposed to samples C2, C4, C6 and C8. These groups corresponded to samples with different sweetness. Sample configuration from Cluster 3 (relative size 24%, Figure 2 (e)) was also significantly correlated to the consensus, but with a lower RV coefficient (0.656). In this example sample configuration of Cluster 3 showed the highest correlation with dimensions 2 and 3 of the consensus (Table 2).

Similar results were found in Studies 1, 2, 6, 7, 8, and 9. In all of them, at least one of the clusters had a sample configuration in the first two dimensions of the MFA very different to the consensus, and some clusters with sample configurations significantly correlated to the consensus, but with intermediate similarity. The configuration of the different clusters were correlated to different parts of the consensus configuration (Table 2). An exception was Study 3, in which the configuration of both clusters was similar to the consensus. In this study although the RV coefficients between the configurations of both clusters and the consensus were high and significant (Table 2), the configuration of Cluster 2 seemed uni-dimensional. The first dimension of sample configuration of Cluster 2 sorted samples identical to the first dimension of the consensus; however the second dimension of the MFA did not seem to be correlated to the consensus configuration and did not provide relevant information (data not shown).

3.3. Samples' descriptions by consumers

Between 11 and 25 terms were elicited by at least 5% of consumers in the nine Studies. The frequency of mention of those terms was computed for each of the clusters identified in the different studies. Study 5 was the only one for which the frequency of mention of the elicited terms did not differ between the identified clusters (χ^2=25.4, p = 0.187). This was also the study in which the lowest number of terms was used to describe the samples (11).

In the other eight studies, between 16% and 56% of the terms had a significantly different frequency of mention among the clusters (p<0.0485). The studies in which only two clusters were identified (Studies 1, 3 and 8) were the ones that had fewer terms mentioned with different frequency among clusters (16 to 20%). In general, both clusters were correlated to the consensus, and the terms that were used differently by the clusters were not the most frequently mentioned. As an example, results of the chi-square per cell test for Study 3 are shown in Table 3. It is interesting to note that in this study, Cluster 1 had a sample configuration in the first two dimensions of the MFA which discriminated samples according to their caramel aroma (data not shown), and the frequency of mention of *Caramel flavour* was significantly higher for this cluster. The other difference in perception suggested by the samples categorization was sweetness, in this case though, although there was a trend in Cluster 2 to mention *sweet/very sweet* in a higher proportion, it was not significant. These results are further reinforced by the projection of the terms on the first two dimensions of the

MFA (Figure 3), where consumers in Cluster 1 are clearly discriminating *Caramel flavour* from *Vanilla flavour*.

In Studies 2 and 6, more than half of the elicited terms were used differently by the identified clusters. In both studies, sample configurations from different clusters were very heterogeneous. For example, in Study 6, milk desserts were formulated to obtain samples with subtle differences in texture and flavour. Sample configuration from Cluster 1 suggests that consumers located the samples mainly according to their texture, while consumers from Cluster 3 appeared to have given more relevance to samples' sweetness (data not shown). Results from the chi-square per cell test showed that consumers from Cluster 1 used the term *Creamy* more frequently than the other clusters, while the frequency of elicitation of the terms *Very sweet* and *Vanilla flavour* was lower. Moreover, consumers in Cluster 3 used more frequently the terms *Sweet* and *Tasty*, and less frequently the terms *Vanilla flavour* and *Consistent*. On the other hand, consumers from Cluster 2 used less frequently the term *Sweet*, which was on average the most frequently used term in this study. The terms *Vanilla flavour* and *Consistent* were elicited more frequently by this cluster, as well as *Aftertaste*, which was on average the least frequently used term in Study 6. In fact, the term *Vanilla flavour* was used almost exclusively by consumers in Cluster 2. It is important to note that sample configuration from this cluster was not correlated to the consensus sample configuration. These results suggest that consumers in Cluster 2 might have used a different criteria in the projective mapping task, and their perception was not reflected in the consensus configuration. Similar results were found for Studies 7 and 9 but detailed information is not provided.

4. Discussion

In the present work consumer segmentation in projective mapping was explored in nine studies with different product categories. Between 2 and 4 groups of consumers were identified and, in the majority of the studies, sample configurations and consumers' descriptions differed among the groups. In most studies the RV coefficients computed between sample configurations of the different clusters were low and not significant, indicating different criteria for estimating global similarities and differences among samples and, consequently, in the relative relevance they gave to the sensory characteristics of the products. Similar results have been reported when analyzing consumer responses to sorting tasks (Courcoux, Faye & Qannari, 2014).

Different factors can underlie consumer heterogeneity in the evaluation of similarities and differences among products. One of the most important factors that could largely contribute to heterogeneity in responses to projective mapping tasks is individual differences in preferred ways of processing information (Allport, 1937). Consumers can be characterized as mostly wholistic if they have a tendency to organize and process information at the global level, while analytic consumers mostly organize and process information according to separate characteristics (Peterson & Deary, 2006). It could be expected that sample configurations from analytic consumers would be more detailed and based on a larger number of sensory characteristics than those from wholistic consumers. In this sense, research on the influence of cognitive style on results from holistic methodologies could contribute to better understand the cognitive underpinnings of sensory characterization tasks.

One of the questions that arises when studying heterogeneity in projective mapping is if consumer processing of sensory information when evaluating global differences among samples would reflect information processing for reaching hedonic judgments. Jaeger et al. (2000) suggested that a process of synthesis is also involved when consumers are asked to score sample liking. Therefore, synthesis processes would be in charge of creating a summary of sensory characteristics of the samples to evaluate global differences and to evaluate how much they like the samples. If the same process is used for evaluating global differences and liking, the main sensory characteristics responsible for perceived similarities and differences among samples would also be the main drivers of liking. However, Torri et al. (2013) reported a weak correspondence between projective mapping and internal preference mapping in wine, which indicates that different synthesis process might be used by consumers to complete hedonic and projective mapping tasks. Further research is needed in this field to study the relationship between perceived similarities and differences among samples and liking.

Familiarity, knowledge and experience with the product have been reported to affect responses to projective mapping tasks (Nestrud & Lawless, 2008; Torri, Dinnella, Recchia, Naes, Tuorila, & Monteleone, 2013). It could be hypothesized that the influence of these variables would be more relevant in complex products, such as wine or olive oil. In this sense, further research is necessary on the interplay between involvement and product complexity on consumers' perception of global similarities and differences among products.

Another point of difference could arise from actual differences in perception, for example taster status or threshold of aroma detection; physiological and perceptual differences between groups would be another interesting point to better understand in relation to categorization. For example, in Study 1 the information provided by one of the consumer groups (Cluster 1) was not well represented in the first four dimensions of the consensus configurations, which could be due to the fact that this group did not discriminate among samples and located the samples randomly.

In most of the studies analyzed in the present work consensus configurations in the first two dimensions were highly similar to the configuration of one of the clusters, and very different to the others. This suggests that the information provided by some of the clusters may not be well represented by the first dimensions of the consensus configuration and could potentially underestimate the complexity of consumers' sensory perception of samples. The cluster with the highest similarity with the consensus was not necessarily the largest one but that with the highest percentage of variance explained by the first dimension (Table 2). Besides, in the majority of the studies the clusters' sample configurations in the first two dimensions of the MFA were correlated to different parts of the consensus configuration (Table 2). These results suggest that the consensus configuration may jeopardize results interpretation as it might overestimate the perception of consumers with the simplest configurations, i.e. those who considered less sensory characteristics for estimating the similarities and differences among samples. Therefore, higher dimensions of the MFA might represent the criteria considered by some consumer groups to evaluate similarities and differences among samples. In this sense, it is interesting to highlight that when projective mapping is used for sensory characterization in new product development the consensus configuration may not always be representative of the perception of the majority of the consumers.

There were studies in which consumers in different clusters clearly gave more relevance to different sensory characteristics, but all clusters were well represented by the consensus configuration. Such is the case of Study 3, where Cluster 2 discriminated mainly two groups of samples according to their sweetness, while Cluster 1 discriminated samples with caramel aroma from the milk desserts with vanilla aroma. In the consensus configuration, samples location in the first dimension of the MFA was closely related to sample configuration from Cluster 2, whereas the position on the second dimension resembled sample configuration from Cluster 1. This stresses that segmentation in projective mapping studies might enable the identification consumer groups that give different relative importance of the sensory characteristics of samples to assess their similarities and differences.

Finally, it is important to note that in this exploratory research all the projective mapping studies considered had 6 or 8 samples, while 5 to 32 samples have been reported in 41 studies published in scientific literature since 1994 up to date. Further research would be necessary to explore consumer segmentation in projective mapping tasks with a larger number of samples.

5. Conclusions

Results from the present work provided evidence of consumer segmentation in projective mapping tasks, suggesting that different consumer groups used different criteria for evaluating global similarities and differences among samples. The consensus configuration was strongly correlated to the configuration of the consumer group with the highest percentage of variance explained by the first dimension. On the other hand, the information provided by some consumer groups was underrepresented in the first two dimensions of the consensus sample configuration, suggesting the need to consider higher dimensions of the

MFA. These results indicate the need to further explore segmentation when analyzing data from projective mapping tasks and to further study the relationship between consumers' holistic perception of products and preference patterns.

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Figure captions

Figure 1. Sample configurations in the first and second (a) and in the third and fourth (b) dimensions of the MFA for the consensus, and sample configurations in the first and second dimensions of the MFA for the three clusters identified in Study 4: Cluster 1 (c), Cluster 2 (d) and Cluster 3 (e).

Figure 2. Sample configurations in the first and second (a) and third and fourth (b) dimensions of the MFA for the consensus and the three clusters identified in Study 5: Cluster 1 (c), Cluster 2 (d) and Cluster 3 (e).

Figure 3. Projection of consumer descriptions in the first and second dimensions of sample space of the MFA for the consensus (a) and the two clusters identified in Study 3: Cluster 1 (b) and Cluster 2 (c). Terms in bold italic correspond to those with square cosine on either the first of second dimension of at least 0.45.

Tables

Table 1. Description of the data sets used to evaluate consumer segmentation on data from projective mapping.

Study ID	Product	Number of samples	Number of consumers
1	Plain crackers	8	91
2	Plain crackers	8	89
3	Vanilla milk desserts	8	101
4	Vanilla milk desserts	8	100
5	Vanilla milk desserts	8	100
6	Vanilla milk desserts	8	100
7	Powdered drinks	6	102
8	Powdered drinks	6	101
9	Yogurt	8	81

Table 2. Summary of the results from hierarchical cluster analysis and Multiple Factor Analysis performed on the projective mapping data of the complete data sets and the clusters identified in each study.

Study ID	Group	Relative size of the clusters (%)	Variance explained by the first two dimensions of the MFA (%)		Cumulative explained variance by the first two dimensions of the MFA(%)	Correlation between the Clusters' and consensus configuration in the first two dimensions of the MFA		Best correlation between the first two dimensions of the Clusters' MFA and two dimensions of the consensus configuration		
			Dim 1	Dim 2		RV	p-value	Dimensions	RV	p-value
1	Consensus	-	46.7	13.6	60.3	-	-	-	-	-
	Cluster 1	41.8	24.4	20.2	44.5	0.557	**0.034**	2,3	0.683	**0.005**
	Cluster 2	58.2	66.8	8.7	75.5	0.975	**0.005**	1,2	0.975	**0.005**
2	Consensus	-	23.0	17.4	40.4	-	-	-	-	-
	Cluster 1	24.7	35.9	17.8	53.7	0.286	0.415	2,3	0.794	**0.001**
	Cluster 2	22.5	51.7	15.6	67.3	0.778	**0.004**	1,2	0.778	**0.004**
	Cluster 3	40.4	26.3	19.9	46.2	0.645	**0.013**	1,2	0.645	**0.013**
	Cluster 4	12.4	50.9	16.0	66.9	0.126	0.784	3,4	0.673	**0.010**
3	Consensus	-	50.6	14.7	65.3	-	-	-	-	-
	Cluster 1	45.5	27.2	25.0	52.2	0.831	**0.002**	1,2	0.831	**0.002**
	Cluster 2	54.5	75.4	6.7	82.0	0.955	**0.005**	1,2	0.955	**0.005**
4	Consensus	-	44.6	21.3	65.9	-	-	-	-	-
	Cluster 1	30.0	46.3	20.2	66.5	0.759	**0.009**	2,3	0.769	**0.005**
	Cluster 2	52.0	68.4	12.2	80.5	0.958	**0.002**	1,2	0.958	**0.002**
	Cluster 3	18.0	40.1	19.9	60.0	0.317	0.303	3,4	0.753	**0.005**
5	Consensus	-	31.2	19.8	51.0	-	-	-	-	-
	Cluster 1	46.0	54.3	10.6	64.9	0.896	**0.003**	1,2	0.896	**0.003**
	Cluster 2	30.0	28.1	21.5	49.6	0.073	0.928	3,4	0.854	**0.001**
	Cluster 3	24.0	49.4	15.6	65.0	0.656	**0.015**	2,3	0.639	**0.043**

Values in bold mean significant RV coefficients (permutation test)

Table 2 (cont.). Summary of the results from hierarchical cluster analysis and Multiple Factor Analysis performed on the projective mapping data of the complete data sets and the clusters identified in each study.

Study ID	Group	Relative size of the clusters (%)	Variance explained by the first two dimensions of the MFA (%)		Cumulative explained variance by the first two dimensions of the MFA(%)	Correlation between the Clusters' and consensus configuration in the first two dimensions of the MFA		Best correlation between the first two dimensions of the Clusters' MFA and two dimensions of the consensus configuration		
			Dim 1	Dim 2		RV	p-value	Dimensions	RV	p-value
6	Consensus	-	29.6	27.0	56.6	-	-	-	-	-
	Cluster 1	29.0	64.5	11.2	75.7	0.782	**0.006**	2,3	0.828	**0.004**
	Cluster 2	44.0	26.6	21.9	48.6	0.513	0.067	1,3	0.669	**0.011**
	Cluster 3	27.0	63.5	11.6	75.1	0.719	**0.010**	1,2	0.719	**0.010**
7	Consensus	-	34.0	25.0	59.0	-	-	-	-	-
	Cluster 1	16.7	62.6	15.4	78.0	0.644	**0.029**	2,3	0.803	**0.018**
	Cluster 2	33.3	30.5	24.1	54.6	0.638	**0.031**	1,4	0.683	**0.041**
	Cluster 3	22.5	70.6	11.3	81.9	0.848	**0.004**	1,2	0.848	**0.004**
	Cluster 4	27.5	40.7	25.8	66.5	0.420	0.407	1,3	0.678	**0.058**
8	Consensus	-	52.7	19.7	72.4	-	-	-	-	-
	Cluster 1	52.5	33.6	27.2	60.8	0.912	**0.002**	1,2	0.912	**0.002**
	Cluster 2	47.5	78.0	9.9	88.0	0.966	**0.007**	1,2	0.966	**0.007**
9	Consensus	-	26.3	20.8	47.2	-	-	-	-	-
	Cluster 1	16.0	42.07	15.62	57.7	0.141	0.803	3,4	0.732	**0.003**
	Cluster 2	25.9	54.43	13.15	67.6	0.604	**0.031**	2,3	0.881	**0.002**
	Cluster 3	25.9	30.48	21.88	52.4	0.122	0.866	3,4	0.531	**0.048**
	Cluster 4	32.1	62.22	10.02	72.2	0.772	**0.008**	1,2	0.772	**0.008**

Values in bold mean significant RV coefficients (permutation test)

Table 3. Results of the chi-square per cell test performed on the terms elicited in Study 3.

Terms	Total number of mentions		
	Cluster 1	**Cluster 2**	**Total**
Notmuchflavourintensity	55	95	150
Sweet	57	80	137
Verysweet	56	70	126
Notverysweet	47	58	105
Vanillaflavour	34	40	74
Tasty	13 (-) *	35 (+) *	48
Disgusting	19	24	43
Consistent	26 (+) **	15 (-) **	41
Creamy	19	20	39
Nice	16	22	38
Runny	15	19	34
Bitter	15	14	29
Intense flavour	6	15	21
Caramel flavour	13 (+) *	7 (-) *	20
Notsweet	3	9	12
Total	394	523	917

(+) or (-) indicate that the observed value is higher or lower than the value predicted by the chi-square distribution.

** $p< 0.01$ and * $p < 0.05$; effect of the chi square per cell.

Figure 1

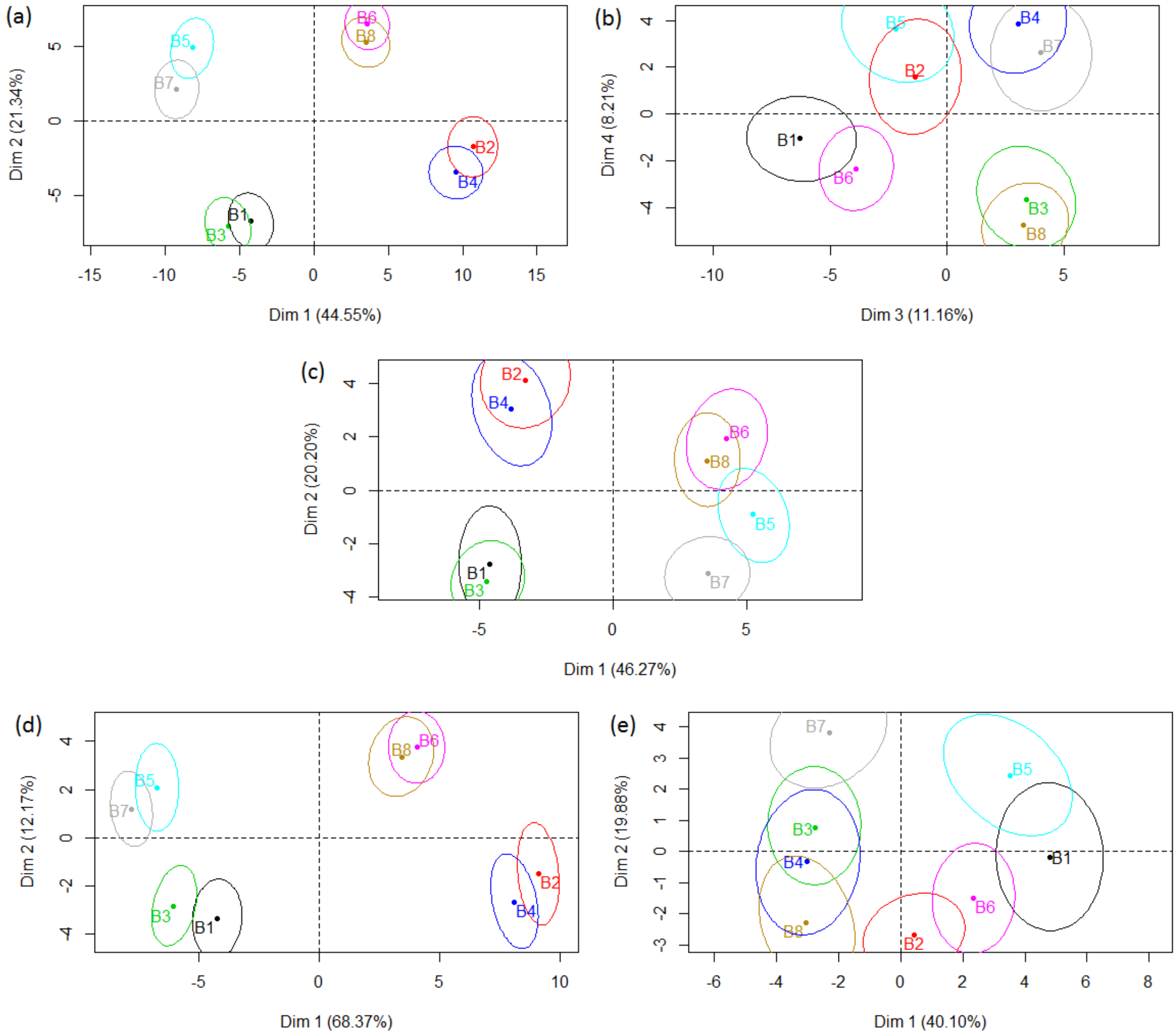
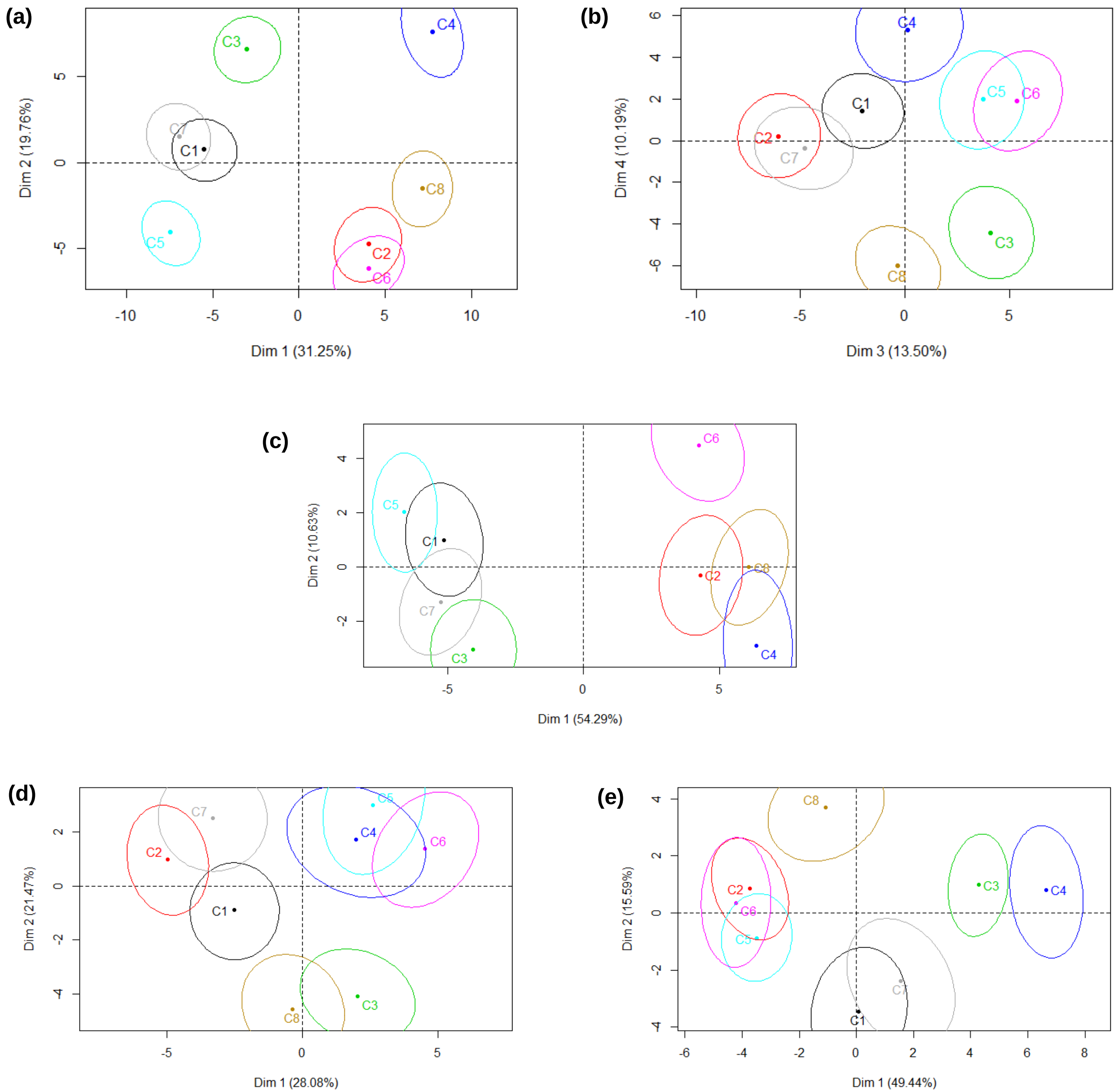
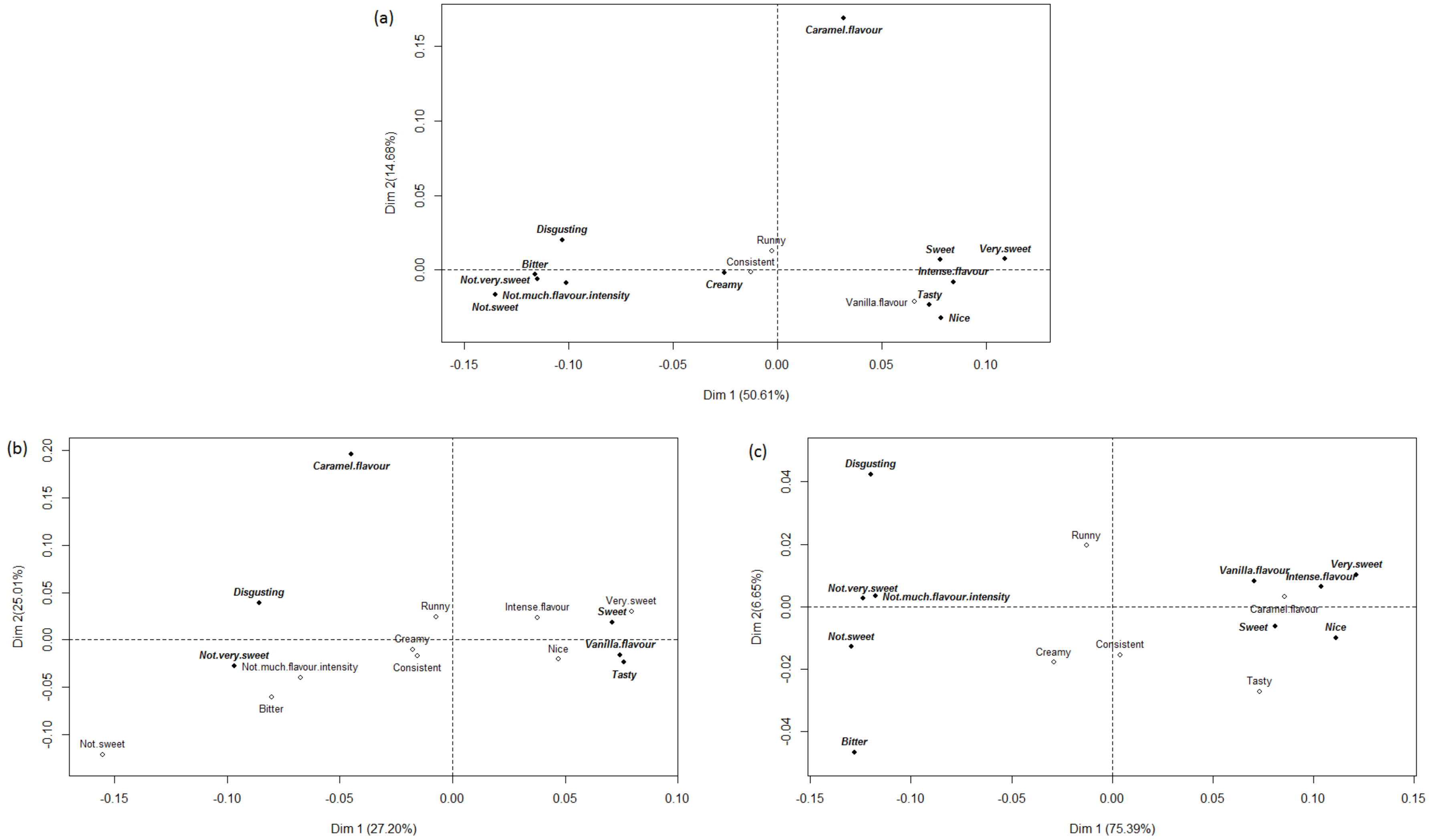

(a)
Dim 1 (44.55%)
Dim 2 (21.34%)
B1
B2
B3
B4
B5
B6
B7
B8
(b)
Dim 3 (11.16%)
Dim 4 (8.21%)
(c)
Dim 1 (46.27%)
Dim 2 (20.20%)
(d)
Dim 1 (68.37%)
Dim 2 (12.17%)
(e)
Dim 1 (40.10%)
Dim 2 (19.88%)

Figure 2



(a)
(b)
(c)
(d)
(e)
Dim 1 (31.25%)
Dim 2 (19.76%)
Dim 3 (13.50%)
Dim 4 (10.19%)
Dim 1 (54.29%)
Dim 2 (10.63%)
Dim 1 (28.08%)
Dim 2 (21.47%)
Dim 1 (49.44%)
Dim 2 (15.59%)
C1
C2
C3
C4
C5
C6
C7
C8


(a)
Caramel.flavour
Disgusting
Runny
Consistent
Sweet
Very.sweet
Bitter
Intense.flavour
Not.very.sweet
Creamy
Not.much.flavour.intensity
Tasty
Vanilla.flavour
Not.sweet
Nice
Dim 2(14.68%)
Dim 1 (50.61%)
(b)
Caramel.flavour
Disgusting
Runny
Intense.flavour
Very.sweet
Sweet
Creamy
Nice
Vanilla.flavour
Not.very.sweet
Not.much.flavour.intensity
Consistent
Tasty
Bitter
Not.sweet
Dim 2(25.01%)
Dim 1 (27.20%)
(c)
Disgusting
Runny
Very.sweet
Vanilla.flavour
Intense.flavour
Not.very.sweet
Not.much.flavour.intensity
Caramel.flavour
Not.sweet
Sweet
Nice
Consistent
Creamy
Tasty
Bitter
Dim 2(6.65%)
Dim 1 (75.39%)