UNDERSTANDING METHODS FOR INTERNAL AND EXTERNAL PREFERENCE MAPPING AND CLUSTERING IN SENSORY ANALYSIS

by

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B.S., King Mongkut's Institute of Technology Ladkrabang, 1998
M.S., Kansas State University, 2006

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Human Nutrition
College of Human Ecology

KANSAS STATE UNIVERSITY
Manhattan, Kansas

2011

Abstract

Preference mapping is a method that provides product development directions for developers to see a whole picture of products, liking and relevant descriptors in a target market. Many statistical methods and commercial statistical software programs offering preference mapping analyses are available to researchers. Because of numerous available options, there are two questions addressed in this research that most scientists must answer before choosing a method of analysis: 1) are the different methods providing the same interpretation, co-ordinate values and object orientation; and 2) which method and program should be used with the data provided?

This research used data from paint, milk and fragrance studies, representing complexity from lesser to higher. The techniques used are principal component analysis, multidimensional preference map (MDPREF), modified preference map (PREFMAP), canonical variate analysis, generalized procrustes analysis and partial least square regression utilizing statistical software programs of SAS, Unscrambler, Senstools and XLSTAT. Moreover, the homogeneousness of consumer data were investigated through hierarchical cluster analysis (McQuitty's similarity analysis, median, single linkage, complete linkage, average linkage, and Ward's method), partitional algorithm (k-means method), nonparametric method versus four manual clustering groups (strict, strict-liking-only, loose, loose-liking-only segments). The manual clusters were extracted according to the most frequently rated highest for best liked and least liked products on hedonic ratings. Furthermore, impacts of plotting preference maps for individual clusters were explored with and without the use of an overall mean liking vector.

Results illustrated various statistical software programs were not similar in their oriented and co-ordinate values, even when using the same preference method. Also, if data were not highly homogenous, interpretation could be different. Most computer cluster analyses did not segment consumers relevant to their preferences and did not yield as homogenous clusters as manual clustering. The interpretation of preference maps created by the highest homogeneous clusters had little improvement when applied to complicated data. Researchers should look at key findings from univariate

data in descriptive sensory studies to obtain accurate interpretations and suggestions from the maps, especially for external preference mapping. When researchers make recommendations based on an external map alone for complicated data, preference maps may be overused.

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Acknowledgements

I would like to dedicate this dissertation to my parents and to my U.S. parents, Dr. Donald and Lorene J. Stuteville, for their encouragement and support throughout my study. Thank you, moms and dads, for being patient with me through waiting for my graduation day to come. And, thank you to my brother for taking care of all family difficulties that happened during my absence. I am particularly grateful Dr. Koushik Adhikari for training me on the use of statistical software programs and for always being willing to face the program's problems with me; Dr. Johnson E. Dallas for solving and guiding me in unconventional programming use of the SAS language; and Dr. Edgar Chambers IV for guidance in organizing, structuring and improving ideas to complete these papers for the Ph.D. program. I would also like to thank Dr. Carrita A. Hightower and her family for always being on my side and encouraging me to stay in the program and keep focused on graduation. Lastly, I would like to thank you Ms. Kat Vesom, Mrs. Juli Anna Vonderharr, Ms. Aussama Soontrunnarudrungsri and Ms. Alicia K. Jenkins for helping me solve my language difficulties and for answering my eccentric questions.

Chapter 1

CHAPTER 1 - Literature Review

Preference mapping was first developed by Chang and Carroll 1969, Carroll 1972, and Schiffman *et al.* 1981. Further development was done by Stone and Sidel 1985, Meilgaard 1991, and Ennis 2001. However, it was first applied to studies in Psychometry by Schlich 1995, and currently it is a well-known procedure used in social behavior sciences, business, marketing, (Green and Rao 1972), product development, and sensory analysis.

The graphical display of a preference map created by multivariate analysis methods is a plot of component scores (product co-ordinations) versus consumers and/or attributes vectors that are derived through the distances of the data matrices in a geometric space. Preference mapping allows researchers to understand influences of attributes on consumer liking (Michon *et al.* 2010; Sinesio *et al.* 2010), differences among products (Villanueva *et al.* 2009; Felberg *et al.* 2010), and segments of products and consumers (Sveindóttir *et al.* 2009; Oupadissakoon *et al.* 2010). Additionally, preference maps and their co-ordinates are used in predicting new prototypes for industries. The preference mapping method has been called by many different names: perceptual mapping, structural segmentation, brand mapping, behavioral mapping, market mapping, product mapping, goal mapping, image mapping, and semantic mapping. However, it is questionable whether all these names refer to the same map that is created from a multivariate technique (Neal 1988). Different statistical procedures are used in the creation of a preference map (e.g., Stochastic ultrametric purchase tree [sculptre analysis], multiple correspondence analysis, multidimensional scaling [MDS], internal preference mapping, external preference mapping, principal component analysis [PCA], statistical shape analysis, Procrustes analysis, superimposition analysis, bi-linear modeling, partial least square regression [PLS] and structural segmentation). All of these analyses are multivariate statistical techniques, but they are based on different theories and some are called by different names although they are the same technique (Neal 1988).

What is Preference Mapping in Sensory Analysis?

Preference mapping is a perceptual map that describes which attributes contributed to consumer liking by using the relationship distances of consumers' hedonic judgments and/or a matrix of descriptive sensory data (Tanenhaus *et al.* 2005).

Preference mapping has become well recognized as a part of product development in most industry standards. This analysis requires one or two data sets, (a descriptive sensory study and a consumer study), depending on what type of preference mapping analysis is preferred. For internal preference mapping, the process begins with performing PCA or other multivariate analyses on the consumer data. For external preference mapping, the process begins with performing the PCA on descriptive sensory data (Fig.1.1) and the results of the PCA are related to the consumer data.

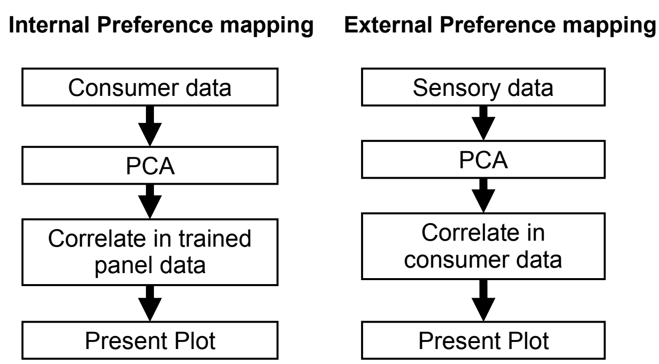


FIG. 1.1 INTERNAL AND EXTERNAL PREFERENCE MAPPING ANALYSIS
(Source: Modified from MacFie 2006).

Examples of internal and external preference maps are shown in Figures 1.2 and 1.4. MacFie (2006) demonstrated the use of internal preference mapping in an apple study (Fig. 1.2) where the map accounted for 39.5% of the variance in consumer liking. It also illustrated that consumers preferred the Royal Gala and Braeburn apples because of the attributes hard, plum/cherry, sweet, yellow or red apple and more acidity.

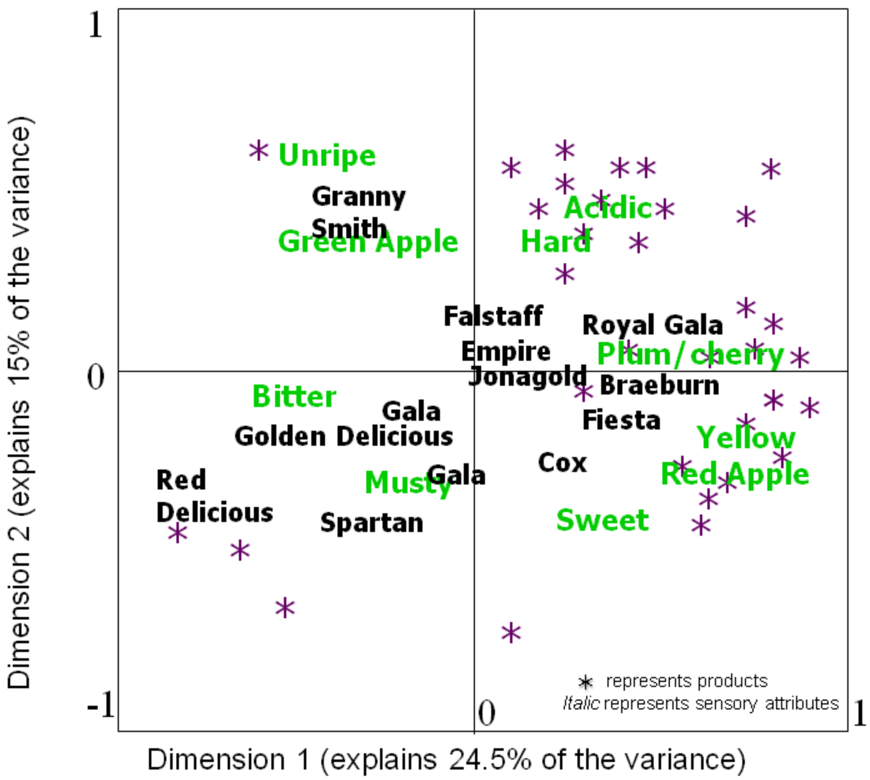


FIG. 1.2 EXTENDED INTERNAL PREFERENCE MAP OF APPLES
(Source: Modified from MacFie, 2006).

An example of an external preference map, is seen in a fragrance study's (Retiveau 2004) where cluster analysis was applied to its sensory data. The samples were clustered into five groups as follows (Fig.1.3): group 1: product *910 and 412;* group 2: *517, 237,947, and 122;* group 3: *513, 814, 359, 861, 219, and 549;* group 4: *318, 196, and 492;* and group 5: *420, 316, 759, 715, and 211*.

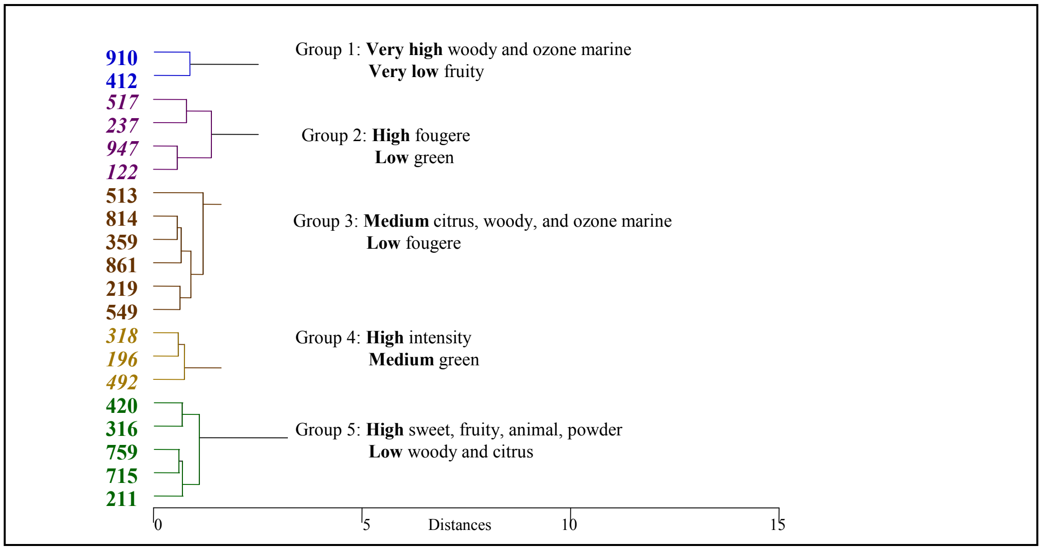


FIG. 1.3 CLUSTER ANALYSIS OF FRAGRANCE STUDY
(Source: Modified from Retiveau 2004).

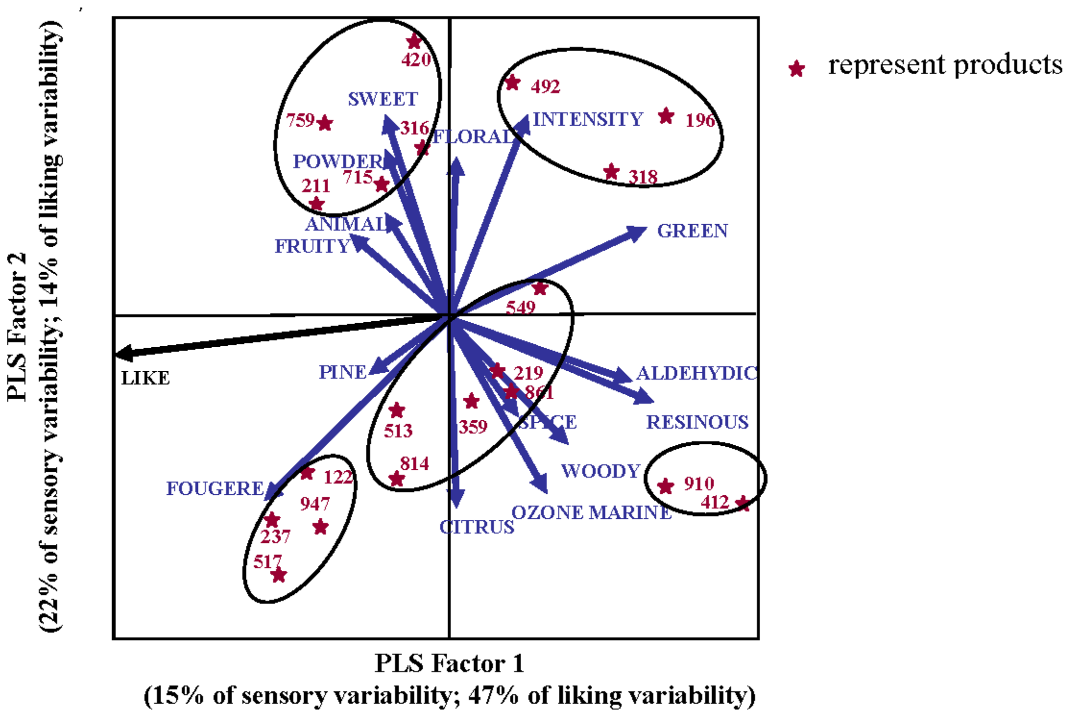


FIG. 1.4 EXTERNAL PREFERENCE MAP OF FRAGRANCE STUDY VIA PLS1
(Source: Modified from Retiveau 2004).

By a partial least square regression (PLS) the external map explained 37% of the sensory variance and 61% of the liking variance (Retiveau 2004). The clusters are also shown in Fig.1.4. The Fougere and pine aromas were the drivers of liking attributes in this study. Samples 517, 237, 947, and 122 were the most preferred products, and were perceived as having high fougere and pine attributes.

These are examples of results yielded by different preference mapping methodologies and different statistical computer software. The usage and a more detailed description will be presented later in this chapter.

Usage of Preference Mapping

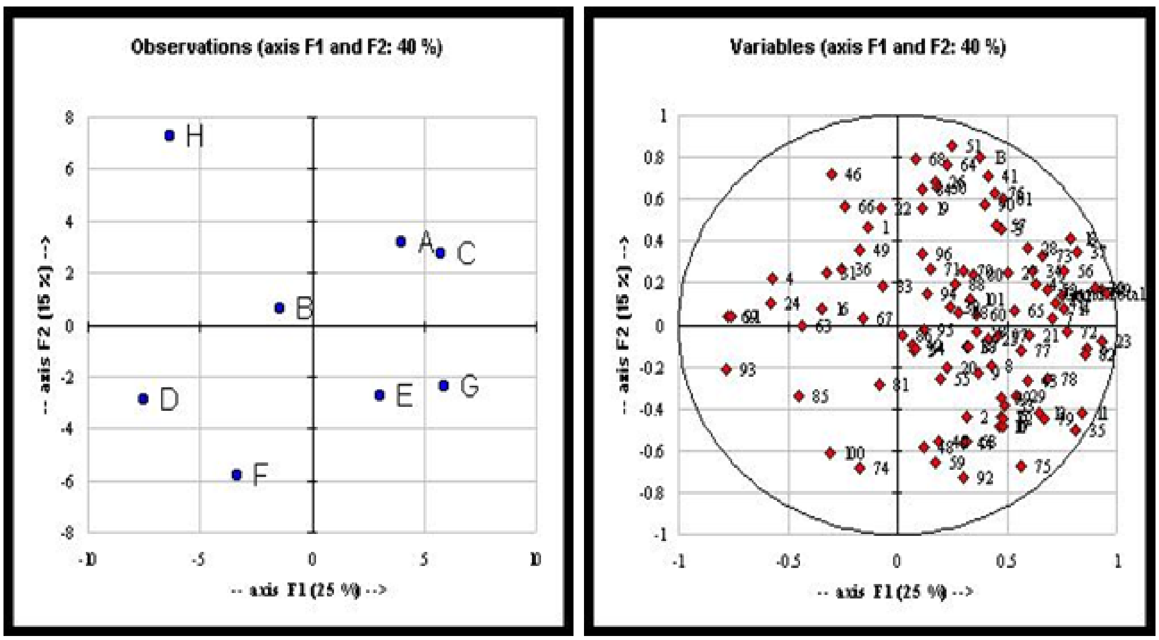
Preference mapping is a useful tool for product developers because the maps help locate the position of a product when comparing it to other products in the market (McEwan 1996; van Kleef *et al.* 2006). Preference mapping also indicates what needs to be done in order to improve a product to meet consumer expectations or desires, therefore, product developers can identify the acceptance ranges of attributes, including the opportunities of a new potential market. Preference mapping also helps optimize the amount of ingredients, and suggests some attributes that can be more influential on the product's acceptability, thus, product developers can obtain more ideas on how they can further develop their products to match with consumer needs (McEwan 1996; van Kleef *et al.* 2006).

Internal Preference Mapping

Internal preference mapping is mainly calculated based on acceptance data, i.e., consumer data. The analysis is obtained via a PCA that uses data from a row (X) × column (Y) matrix. Researchers have two options for carrying the PCA on either the covariance or correlation (Borgonone 2001). However, for sensory data it is recommended to use internal preference mapping with a covariance matrix so consumers with small or zero preferences or low standard deviations will not influence the map structure more than they should (Schlich 1996). The PCA reduces the number of X's into a few principal component factors, which can be explained by those X's that are projected on each component factor. In the case of internal preference mapping, the X rows are the acceptance scores of each consumer, the Y columns are products used in a study and the other ideas remain the same as explained for the PCA

(Greenhoff and MacFie 1994). More detail about PCA can be found in Johnson (1998) and Meullenet *et al.* (2007).

With the highest percentages explaining the variation of the data set, usually 2-4 principal components are plotted in graphic outputs. Once running PCA, the program automatically calculates the loading vectors of X's and component scores of Y's; then the loading and score plots will be created. The score chart is plotted using the components' scores of each sample (Fig. 1.5A) on the principal component axes, while the loading chart is plotted according to the consumers' loading vectors (Fig.1.5B).



A) B)

FIG. 1.5 THE INTERNAL PREFERENCE MAP, THE OUTPUT FROM XLSTAT
Products (A-H) were projected on components 1 (F1) and 2 (F2) as illustrated in map (a). Endpoints of consumer id vectors (if lines were drawn) were shown in map (b).
(Source: MacFie 2006).

Schilch (1995) stated that the internal preference map is intended to determine groups of consumers, who have similar product preferences, through the vectors that are heading in the same direction on the loading map (Fig.1.6).

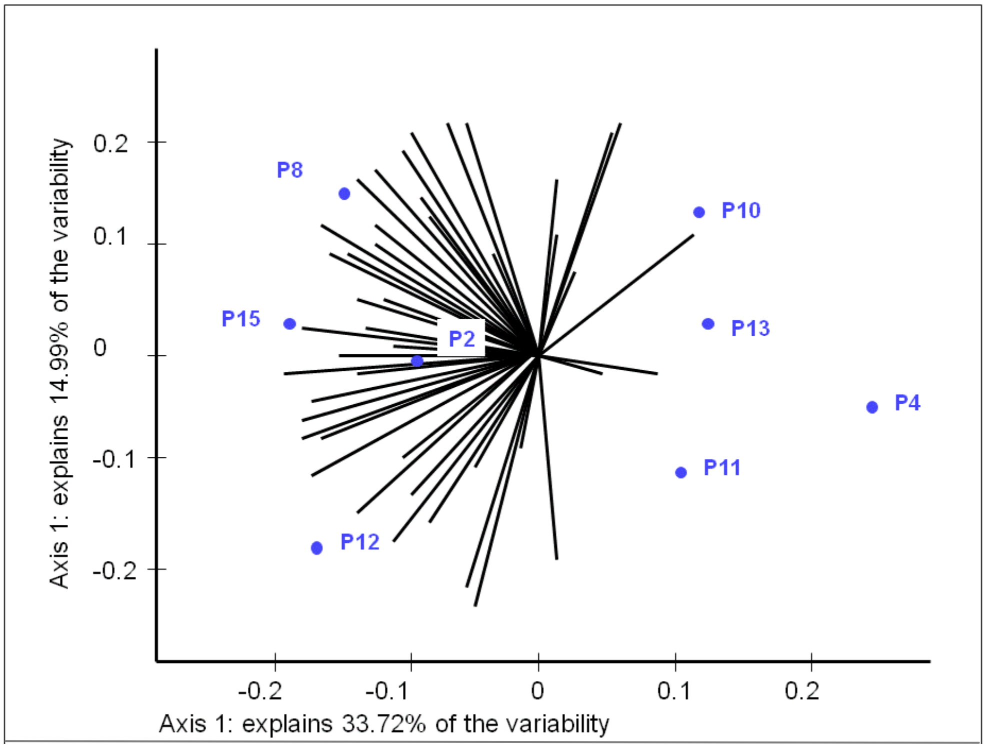


FIG. 1.6 THE INTERNAL PREFERENCE MAP OF CONSUMER REFERENCES FOR COFFEE BY PCA PLOTTED USING ALL INDIVIDUAL CONSUMERS: OUTPUT FROM SAS

The map was plotted based on 80 French consumers' vectors. The first axis explained 33.7 % of the variability in the data where almost all consumers preferred coffees that were in the direction of products 2, 8, 12, and 15. Few consumers preferred coffees in the opposite direction. The second axis explained 15% of the variability in the data where it differentiated between the consumers who favored product 8 from those who favored product 12 (Source: Sahmer *et al.* 2006).

However, it becomes harder to read and interpret when involving large numbers of consumers. To solve this problem Schilch (1995) suggested performing a cluster analysis on consumers by using either consumers' liking scores or demographic information (Fig.1.7).

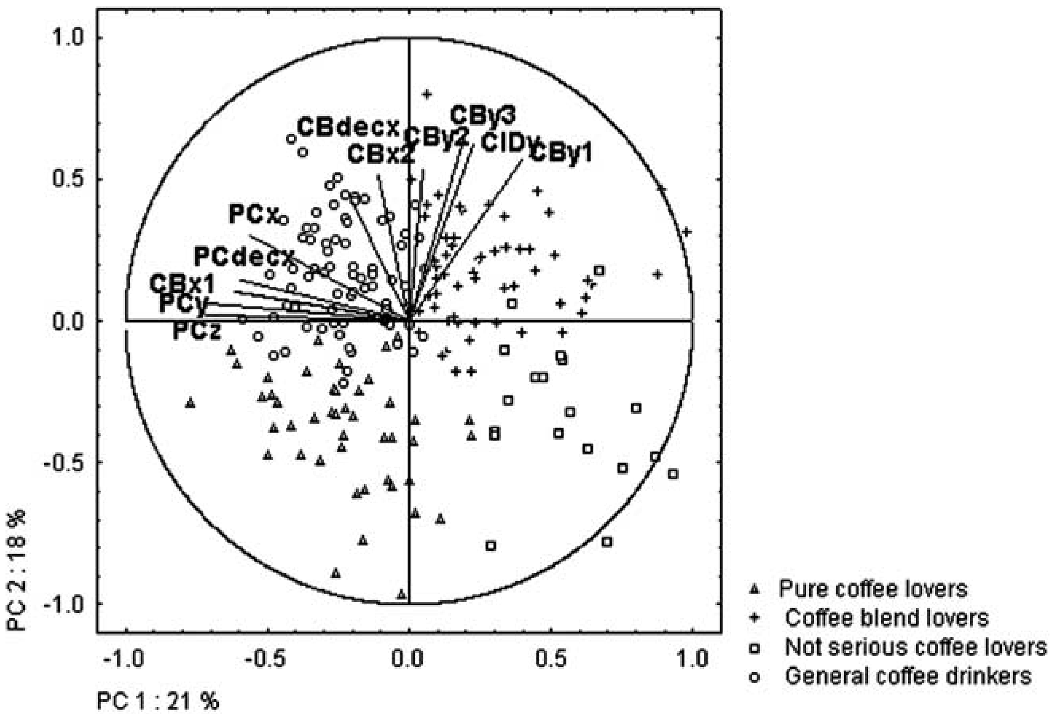


FIG. 1.7 THE INTERNAL PREFERENCE MAP OF CONSUMER PREFERENCES FOR INSTANT COFFEE BY PCA WITH CLUSTERING ALL CONSUMERS, THE OUTPUT FROM SPSS

Principal component 1 (PC1) indicated two clusters of consumers who 1) preferred pure coffee and $CB_{X1,}$ and 2) disliked the stronger flavored pure coffees, but liked coffee blends. Principal component 2 distinguished consumers who liked instant coffee in general from consumers who had other preferences. Consumers were divided by cluster analysis into four groups. In cluster 1, 23% of consumers were "pure coffee lovers;" they rated PC_Z and CB_{Y1} as the least liked coffees. Thirty percent of the consumers in cluster 2 were "instant coffee blend lovers;" they rated pure instant coffees low. Consumers in cluster 3 (10%) were "not serious coffee drinkers." Consumers in cluster 4 were "general coffee drinkers" and represented 37% of the consumers; their ratings were not much different for all the coffee samples in the study (Source: Geel *et al.* 2005).

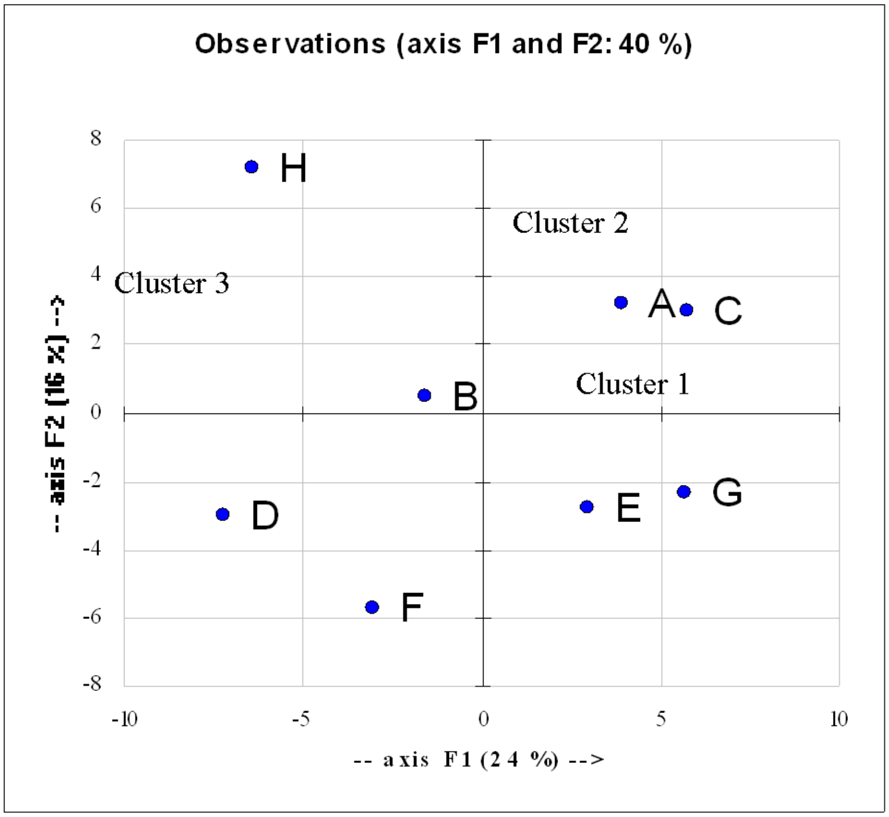


FIG. 1.8 THE INTERNAL PREFERENCE MAP OF CONSUMER PREFERENCES USING MEANS OF DESCRIPTIVE AND HEDONIC SCORES OF EACH CONSUMER CLUSTER, THE OUTPUT FROM XLSTAT
Principal components 1 and 2 (axis F1 and 2) explained 40% of consumer liking. The consumers in cluster 1 and 2 preferred products A and C the most; they disliked products D and F. The consumers in cluster 3 favored product H the most and they disliked products E and G (Source: MacFie 2006).

In addition, Schilch (1995) also stated that performing internal preference mapping on product scores (the coordinates from PCA output) and the means of descriptive data (the mean scores of each attribute), as preferred by some scientist in the UK, would generate a more explicit and easier interpreted map than using the original internal preference mapping technique (Fig.1.8).

In summary, the internal preference map could be created by internal mapping with 1)PCA of all individual consumers, 2) PCA by clustering consumers, or 3) the means of the individual consumer cluster's liking score and the projected descriptors. Applying cluster analysis to consumer data is possible but it may or may not help with a better understanding of the interpretations; this depends on the complexity of the data and the type of products being used. Therefore, comparing preference mapping methods will show whether those methods are different or similar in their conclusions.

Pros and Cons

The advantages and disadvantages of internal preference mapping are as follows:

Advantages

1. Uses all actual hedonic scores (not liking mean scores) to account for the individual differences of consumers (Jaeger *et al.* 2000);
2. Easier to understand than external preference mapping because the method is based on the use of PCA to create a map (McEwan 1996);
3. Helps locate a possible new market (1996);
4. Can indirectly refer to attributes that need changing in order to alter the product position;
5. Can be used to screen or reduce the number of products used in an experiment before proceeding with further analyses (1996).

Disadvantages

1. The variation of data explained by each component often is low (McEwan 1996);
2. There are so many consumers scatter around the map that also has the product overlay interpretation is difficult.

External Preference Mapping

The principle of external preference mapping is to regress the liking data for each consumer, or only their mean scores, against the product's co-ordinates that are obtained from a dimension reduction multivariate analysis (e.g., PCA) of the descriptive sensory study (Greenhoff and MacFie 1994). History of the external preference originates in 1972, when Carroll introduced a polynomial regression of each individual consumer onto the product co-ordinates derived from a dimension reduction method, called external preference mapping (PREFMAP). Each consumer is validated to best fit in one of four regression models, i.e., quadratic, elliptical, circular, or vectorial model (Greenhoff and MacFie 1994). This is the first technique providing a connection between consumer data to the descriptive data. For an detailed explanation, see Schlich (1995), McEwan (1996) and Greenhoff and MacFie (1994).

The multivariate analyses applied to create an external preference map are PCA (Felberg *et al.* 2010; Sinesio *et al*. 2010), PREFMAP (Schlich 1995; Carbonell *et al.* 2008), Canonical variate analysis (CVA; Hein *et al.* 2009), generalized Procrustes analysis (GPA; Carbonell *et al.* 2008; and Nestrud and Lawless 2008), and a variation of PCA techniques, partial least square regression, e.g., PLS1(Narain *et al.* 2004) and PLS2 (Tenenhaus *et al.* 2005).

Details for PCA method are as explained in internal preference mapping, except in the case of external mapping where the X-matrix is composed of sensory-descriptor-intensity scores and product liking mean scores.

CVA was developed by Hotelling (1935). This method is specific to study the linear interrelationship (i.e., canonical correlation) of variables. The CVA searches for the pair of linear combinations (i.e., canonical variates) holding the largest correlation, then searches for the next canonical variate holding the second, third, forth, and so on, largest correlation with the restriction of uncorrelated to the previous combinations (Johnson and Wichern 1988; Johnson 1998). Both PCA and CVA are a generalization of multiple regression analysis on two or more dependent variables. Differences between the two analyses are, “in that the CVA weights between-group differences using the within-group dispersion. Also, the first axis of CVA is not size-related, as it is in PCA,” (Douglas and Matthews 1992).

GPA was developed by Gower (1975); his article demonstrates an example of using rank data to verify if judges evaluated the same or differently from each other. The main purpose of this analysis is studying the results of Free Choice Profiling (judges develop their own descriptors and their definitions to describe products) because other analyses are not appropriate to explore the data (Meullenet *et al.* 2007). The GPA recognizes a sample descriptive profile in a form of initial configuration. The intensity of each descriptor represents a point in the configuration. The approach is finished when two (or more) configurations superimpose.

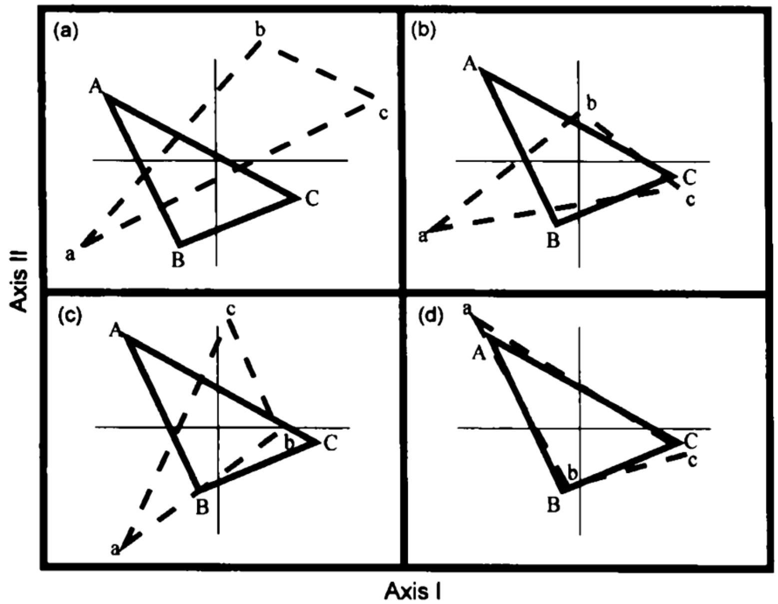


FIG. 1.9 STEPS OF GPA
a) Two initial configurations; b) after translation; c) the triangle ABC is fixed as a reference, while the triangle abc is rotated until the sum-of-squared residuals between the 2-triangle co-ordinates is minimized; and d) after completed superimposition. (Source: Peres-Neto and Jackson 2001).

The GPA processes the data through three steps (Fig.1.9):

1) Translation (centering or standardizing scores to the same origin);
2) Rotation/reflection, if necessary (correcting inconsistent use of terms); and
3) Isotropic scale change (accounts for different ranges).

For more detail, see Dijksterhuis (1996), Arnold and Williams (1986), and Gerber (2005).

The PLS approach was developed by Wold (1982 and 1985); it is recommended to use this approach when there are equal (or more) descriptive variables to types of samples, and in a situation where components are highly correlated. This approach allows easier interpretation of the regression equations (Carrascal *et al.* 2009). Martens and Martens (2001) illustrate that the process begins with reducing the descriptive scores (X-matrix) into a score matrix T for the optimal number of components.

$$T = w(X) \qquad \text{(a)}$$

According to that optimal number of components, the PLS decomposes both descriptive scores (X-matrix) and consumer liking scores (Y-matrix) into T and U matrices with corresponding P and Q loadings and their residual E and F.

$X = 1\overline{X} + TP' + E$ (b)

$Y = 1\overline{Y} + TQ' + F$ (c)

$Y = 1b_0 + XB + F$ (d)

Then the consumer liking scores (Y) are directly modelled from the X-matrix through the coefficient B matrix (estimated function between P and Q loadings) by using ordinary multiple regression (Abdi 2003). Finally, the PLS predicts the consumer liking score (y_i) from equation e.

$y_i = \overline{y} + t_i Q' + f_i;\ f_i \equiv b_0 + x_i B + f_i$ (e)

The PLS differs from PCA in that: 1) the PCA components focus only on maximizing the variance explained in a descriptive attribute matrix, but the PLS components focus on maximizing the covariance between those two matrices, and 2) the PLS seeks common components that “perform simultaneous decomposition” (Martens and Martens 2001). The common types used in sensory studies are PLS1 (one data matrix is a single column of mean liking) and PLS2 (two data matrices are multidimensional; Rosipal and Krämer 2006; Tang *et al*. 2000).

After obtaining the co-ordinates of products, descriptors, and consumers, they are superimposed into one map, known as a biplot (e.g., Fig.1.4, and 1.10-1.14).

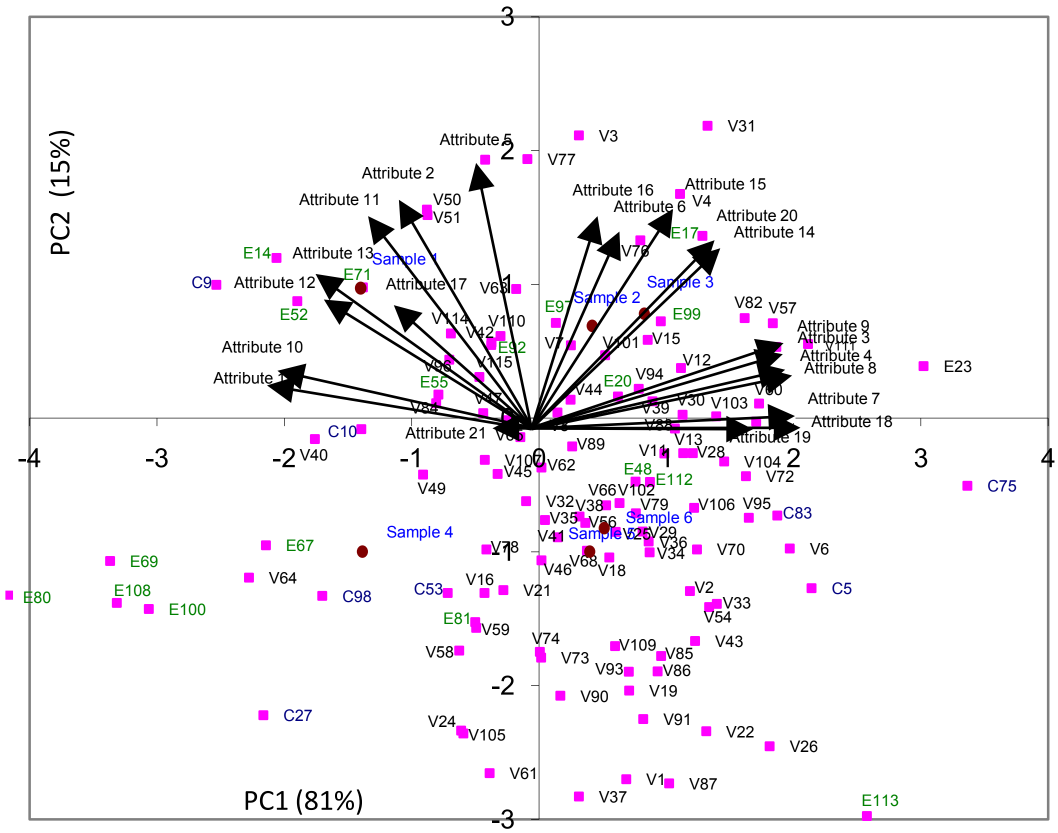


FIG. 1.10 PREFMAP BIPLOT SHOWING RELATIONSHIPS OF SIX PRODUCTS, 21 DESCRIPTIVE ATTRIBUTES AND 115 CONSUMERS ON THE FIRST TWO DIMENSIONS

(V, C, E and Q were consumer ids whom fitted by a vector, circular, and elliptical model, respectively).

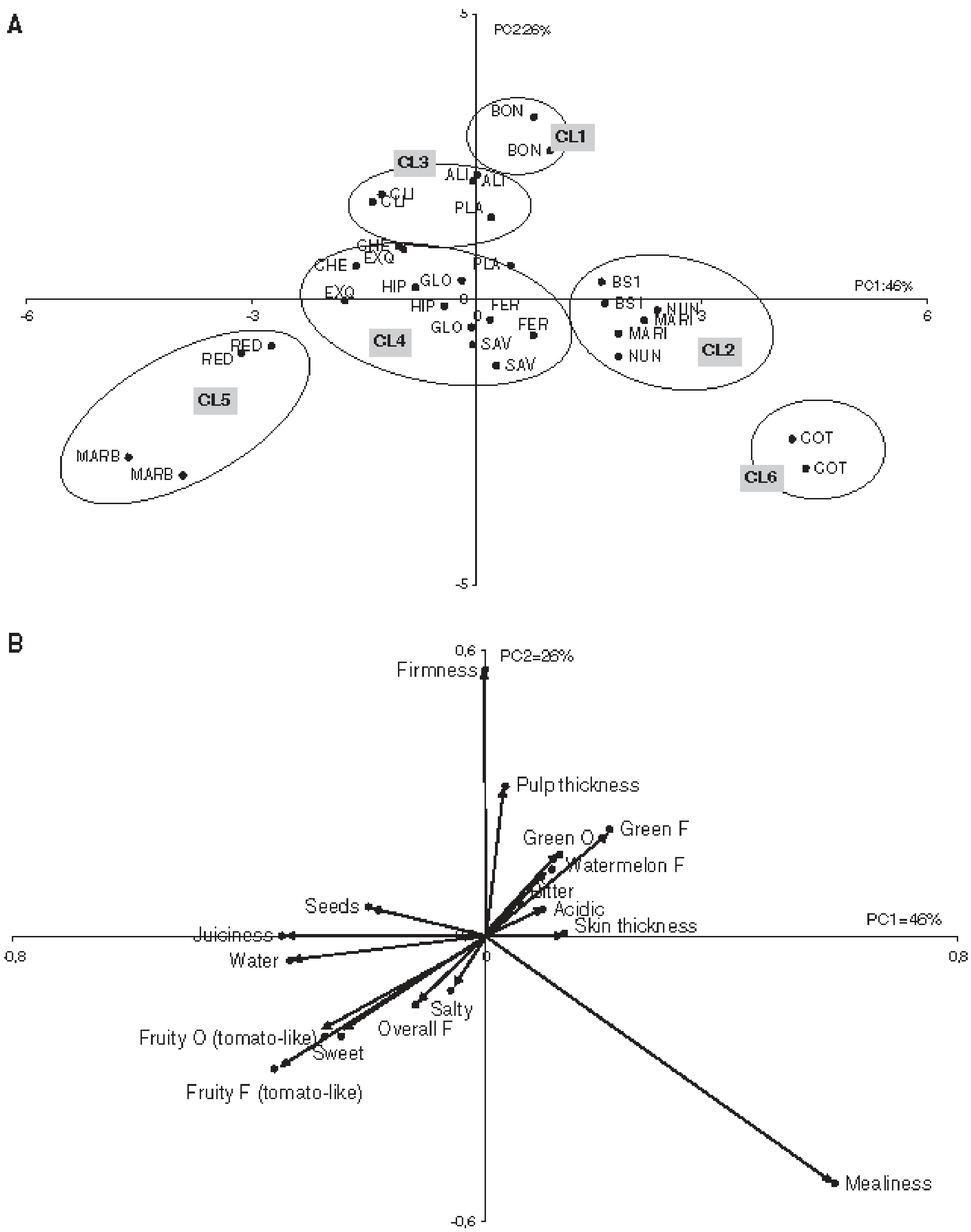


FIG. 1.11 PCA BIPLOT SHOWING MEANS OF CONSUMER ACCEPTANCE AND DESCRIPTIVE ATTRIBUTES OF FRENCH AND DUTCH TOMATO CULTIVARS BY ITALIAN CONSUMERS

A) Mean liking vectors of individual clusters and samples configuration and B) descriptors plot. Tomato samples grown in the Netherlands are in bold alphabets and in the France are in regular alphabets. (Source: Sinesio *et al.*2010).

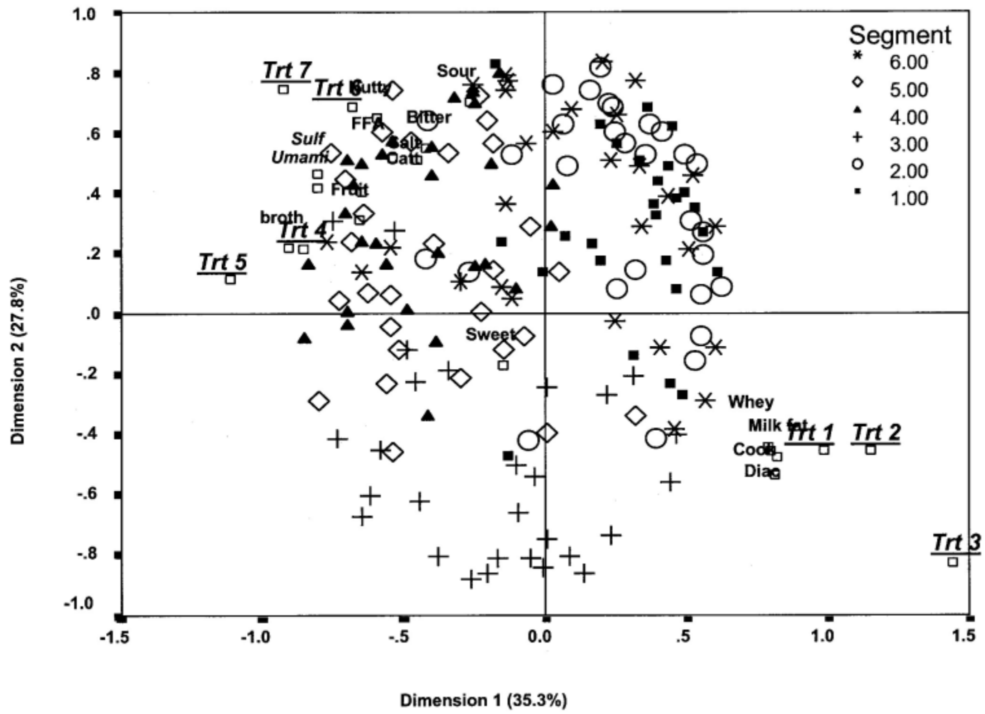


FIG. 1.12 GPA PREFERENCE BIPLOT OF SEVEN CHEDDAR CHEESES VARYING IN MATURITY LEVEL, 15 DESCRIPTIVE ATTRIBUTES AND SIX CONSUMER CLUSTERS

(Source: Young *et al.* 2004).

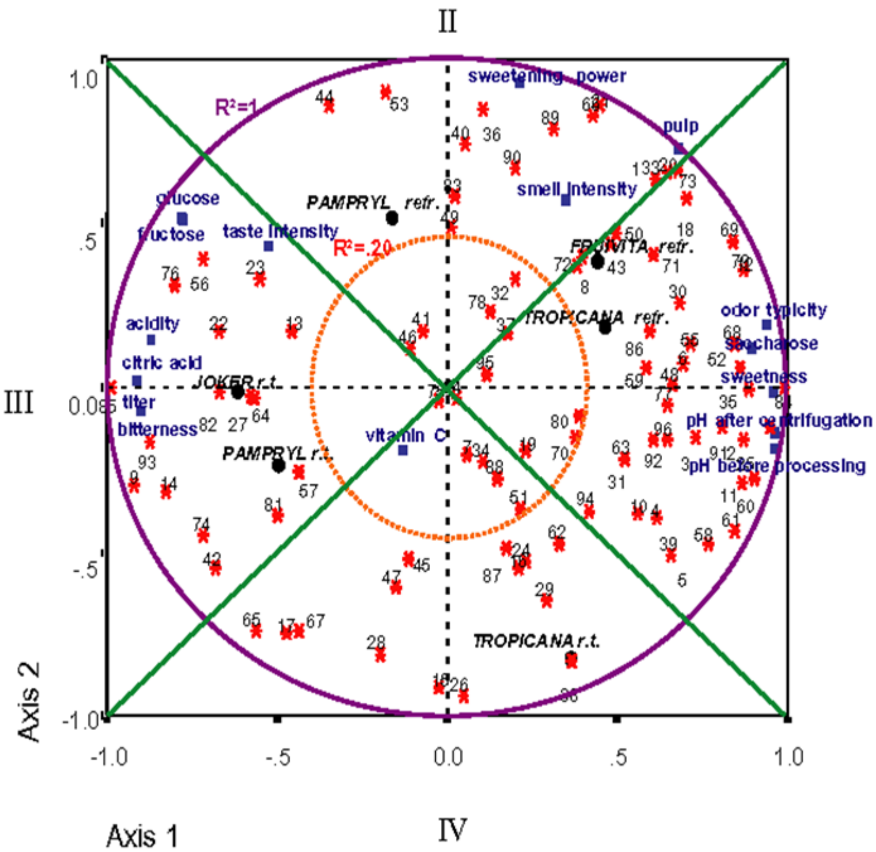


FIG. 1.13 PLS2 BIPLOT SHOWING RELATIONSHIPS OF SIX SAMPLES, HEDONIC JUDGEMENTS (96 CONSUMERS FOR Y-VARIABLE), AND 16 PHYSIO-CHEMICAL AND SENSORY DESCRIPTORS (X-VARIABLE)
(Source: Tenenhaus *et al.* 2005).

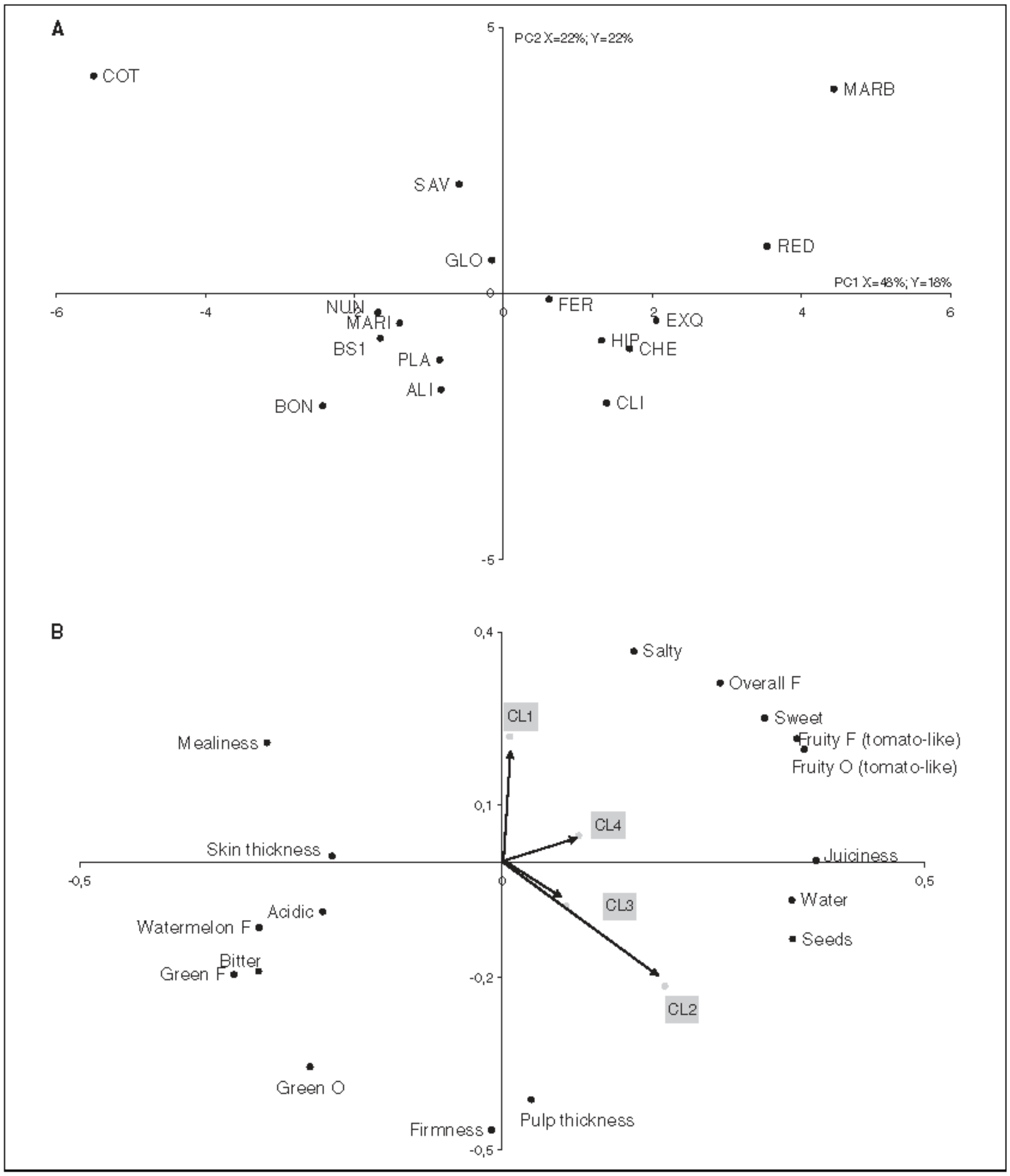


FIG. 1.14 PLS2 PLOTS SHOWING RELATIONSHIPS OF 16 FRESH TOMATO CULTIVARS, HEDONIC JUDGMENTS (FOUR CONSUMER CLUSTERS FOR Y-VARIABLE) AND 18 SENSORY DESCRIPTORS (X-VARIABLE)
(Source: Sinesio *et al.* 2010).

In summary, the external preference map could be created by:

1. PCA with incorporate hedonic mean to X-matrix,
2. Performing PREFMAP on the co-ordinates of PCA, CVA, or GPA,
3. PLS1 with mean liking scores of all consumers,
4. PLS2 with individual consumers or means of individual clusters.

Pros and Cons

The advantages and disadvantages of an external preference mapping are as follows:

Advantages

1. Provides information that contains a connection between descriptive and consumer study to further directions and optimization for product developers (McEwan 1996);
2. Demonstrates what products are available to consumers and other possibilities for new products with sensory descriptors that drive this consumer segment.

Disadvantages

1. When superimposing a descriptor and consumer plot into one map, the product co-ordinations are more relevant to descriptive information than to consumer information. It could provide false descriptors that drive the liking;
2. There are some consumers who are interested in the minor descriptors for responding to their liking. These descriptors may not be described in the percent variance explained from components that create the map (Greenhoff and MacFie 1994);
3. The analysis requires that all consumers evaluate all samples;
4. A map is complex when it contains a large number of samples(McEwan 1996);
5. To get a well represented map requires a good combination of samples to represent the preference-map space; it also requires consumers who can be representatives of target groups and react to sensory variation in the samples.
6. Researchers know descriptive sensory properties, not just products and their market, unlike the results from the internal preference mapping.

Statistical Computing Programs

To perform internal and external preference analysis for researchers there are many statistical computer programs:

1. SAS® (PRINCOMP or MDPREF procedure)

   SAS Institute Inc.

   100 SAS Campus Drive, Cary, NC 27513-2414,

www.sas.com

2. SPSS®

   SPSS Inc.

   233 S. Wacker Drive, 11th Floor, Chicago, IL 60606

   www.spss.com

3. XLSTAT®

   Adinsoft USA

   224 Centre Street, 3rd Floor, New York, NY 10013

   www.xlstat.com

4. SYSTAT®

   Systat Software, Inc.

   501 Canal Blvd, Suite E, Point Richmond, CA 94804-2028

   www.systat.com

5. The R project for statistical computing

   The R Foundation for Statistical Computing

   c/o Institut für Statistik und Wahrscheinlichkeitstheorie

   Technische Universität Wien, Wiedner Hauptstraße 8-10/1071, 1040 Vienna Austria

   www.r-project.org

6. Unscrambler®

   CAMO Software Inc.

   One Woodbridge Center, Suite 319, Woodbridge, NJ 07095 USA

   www.unscrambler.camo.com

7. Senstools®

   OP&P Product Research BV

Utrecht, The Netherlands

www.opp.nl

8. PC-MDS package

    Scott M. Smith, Ph.D., James Passey Professor of Marketing;

    634 TNRB

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Comparing Preference Mapping Methodologies

Williams *et al.* (1988) performed GPA on descriptive sensory data, then correlated the first dimension to chemical/physical data using multiple regression, principal component regression (PCR) and PLS. Williams *et al*. suggested: 1) the GPA scheme presented a more reliable plot of relationships among products, and sensory properties, especially when allowing each panelist to use their own descriptive terminology; and 2) PLS yielded more meaningful information because it incorporated both data variation and correlation with the sensory data.

Hunter and Muir (1995) performed GPA and PCA on a sensory study of cheese samples for texture, flavor and odor; both methods yielded different configurations. Comparisons on the sample plots showed a high degree of similarity for texture, much less agreement for flavor and a high degree of difference for odor. The reliability of the sample co-ordinates was measured through standard errors of the means for each dimension and “the variance ratios for the treatment variation relative to the within treatment variation were considered," (Hunter and Muir 1995). The standard errors of GPA were smaller than for PCA. For example, GPA requires three to four components to explain texture, one for odor, and two for flavor, whereas PCA can justify three components for texture, one for odor, and one for flavor (Hunter and Muir 1995). The variance ratios suggest that the GPA plots better differentiated between the samples.

Adnan *et al.* (2006) observed how well some regression methods handle the problem of multicollinearity. Mendenhall and Sincich (2003) defined multicollinearity as a situation "when two or more of the independent variables used in regression are moderately or highly correlated." This results in over-fitting the regression model and provides invalid results when calculating outcomes from an individual predictor (2003). Adnan *et al.* (2006) concluded that Ridge Regression (RR) and PLS effectively handled the multicollinearity problems better than principal component regression (PCR), and the differences in values were very small. This finding was also the same as the Rougoor *et al.* study that stated "PLS is a good alternative to PCR when relations were complex and the number of observations was small. Advantages of PLS are the optimization towards the Y-variables, resulting in a higher R^2, and the possibility to include more than one Y-variable. Advantages of PCR are that hypothesis testing can be performed, and that complete optimization is used in determining the PCs" (2000).

Chung *et al.* (2003) created maps using the applications of GPA and PLSR and compared them to find whether or not their performance was similar in correlating descriptive sensory and chemical data. They concluded both GPA and PLSR effectively related chemical data with sensory data; PLSR did not present a meaningful plot when calculated from log-transformed chemical data, whereas GPA did.

Van Kleef *et al.* (2006) reviewed literature on comparing internal and external preference mapping methods by including actions that different end-users perceived from preference maps. The authors stated that, 1) internal preference maps were sufficient for marketing use to primarily identify new products; 2) external preference maps provided perceptual attributes and made it easier for food technologists to optimize ingredients; and 3) both maps were recommended for the interface of marketing and product development.

Consumer Segments

Since 1997 there have been more than 400 studies in the *Journal of Sensory Studies* and *Food Quality and Preference* where researchers have used cluster analysis with the aim of segmenting consumers with similar thinking together for understanding their preferences in food and manufacturing products. Three most popular clustering algorithms used in sensory framework are hierarchical, partitional, and density-based (nonparametric) methods (Jain and Dubes 1988; SAS 2005).

Hierarchical Cluster Analysis

Hierarchical clustering classifies consumers into nested subgroups based on dissimilarities in distance measurements between an individual and other consumers. A simple measurement is Euclidean distance (Johnson 1998). After the Euclidean distances between two consumers are calculated, the analysis sorts all distances and places individual consumers into their belonging subgroup according to a consumer's sum of squared distance matrix. Several linkages (e.g., single linkage, complete linkage method, average method, Ward's method, and McQuitty's similarity analysis) are applied to calculate the total differences. The quantity of the differences is used to determine unifying abilities in creating a hierarchy of clusters. Johnson and Wichern (1988) and Adamson and Bawden (1981) illustrated basic theories of similarity measures and linkage methods. In short, they explained the linkage processes as: there are many methods for joining two consumers or groups into one cluster e.g., the single linkage considers minimum distance or nearest neighbor (Sharma and Kumar 2006), the complete linkage considers maximum distance or farthest neighbor (Liggett *et al.* 2008), or, the average linkage considers average distance (Gámbaro *et al.* 2007). The Ward's and McQuitty's methods differ little from the others. Ward's considers joining groups that minimized the information loss, i.e. the total sum of square deviations of every point from the mean of its cluster, (Mahanna and Lee 2010; Felberg *et al.* 2010; Sinesio *et al.* 2010; Sabbe *et al.* 2009; Childs *et al.* 2009). McQuitty's method joins groups based on common similarities among the groups.

Johnson (1998) demonstrated how to perform cluster analysis by using SAS and its interpretations. Meullenet *et al.* (2007) discussed a few approaches to segment consumers into clusters via hierarchical cluster analysis with preference data through options of raw, centered, and standardized data.

Banfield and Raftery (1993) proposed ways to solve limitations that exist in cluster analysis procedures based on maximum likelihood. The three limitations were: 1) analysis prefers constant variance matrices among the clusters, although clusters contain uneven variance; 2) it is appropriate for normal distribution data; and 3) it is sensitive to statistical errors and residuals. Banfield and Raftery's study explains a framework for two-step cluster analysis offered by SPSS. Geeroms *et al.* (2008), and, Sveinsdóttir *et al.* (2009), as examples, applied this method to their consumer studies.

Nonhierarchical Clustering Method (Partitional Algorithm)

While hierarchical clustering is designed to join subgroups until they are all in one group, partitional algorithms are designed to decompose consumers from one large group into k disjoint clusters. A familiar nonhierarchical clustering method is k-means clustering (MacQueen 1967; Tomlins *et al.* 2005; Plaehn and Lundahl 2006; Resano *et al.* 2009). The focus of the k-means method is on minimizing dissimilarity within a cluster and maximizing dissimilarity between clusters (Wajrock *et al.* 2008).

Johnson and Wichern summarized the k-means process as follows:

1. Partition the items into *K* initial clusters.
2. Proceed through the list of items, assigning an item to the cluster whose centroid (mean) is nearest. (Distance is usually computed using Euclidean distance with either standardized or unstandardized observations). Recalculate the centroid for the cluster receiving the new item, and for the cluster losing the item.
3. Repeat Step 2 until no more reassignments take place (1988).

Density-based (Nonparametric) Clustering Method

The density-based algorithm "is designed to discover clusters of arbitrary shape as well as to distinguish noise," (Sander *et al.* 1998); for further exploration see Ester *et al.* (1996 and 1997) and SAS (2005). A simple explanation stated by Dash *et al.* (2001) is that this algorithm defines clusters by their higher density of consumers rather than by the cluster's surrounding area. The algorithm does not require a specific number of clusters to begin the process, but instead it needs the number of neighbors or maximum radius of the sphere to begin calculation. This algorithm is not a popular tool in sensory science, as of yet, thus was found in only one study (MacKay and O'Mahony 2002) to date. One way to operate the nonparametric clustering is by using SAS PROC MODECLUS, method =1.

Another variant of the density-based algorithm is a latent cluster analysis, i.e., two-stage (variable) clustering, SAS PROC VARCLUS or PROC CLUSTER method = twostage. The two-stage cluster analysis is composed of two steps. The first step, a hierarchical clustering method, is applied to the correlation-distance matrix to predefine a cluster number; these clusters are called global clusters. The last step takes those global clusters and applies the latent variable method by calculating global cluster components, thus creating sub-clusters of each global cluster. This in turn creates a global cluster structure and forms a single tree of variable clusters (Lee *et al.* 2008).

Comparing Clustering Algorithm

The most popular clustering methods for consumer studies are: 1) hierarchical algorithm, especially Ward's method; and 2) partitional algorithm, i.e., k-means method.

Meilă and Heckerman (1998) compared three clustering algorithms: expectation maximization (EM) algorithm, classification EM (CEM) reminiscent of k-means, and hierarchical cluster analysis. "The EM clustering algorithm computes probabilities of cluster memberships based on one or more probability distributions. The goal of the clustering algorithm then is to maximize the overall probability or likelihood of the data, given the (final) clusters" (StatSoft Inc. 2010). The CEM incorporates a classification step before maximizing the likelihood of the data, (Samé *et al*. 2007). Performance criteria were measure for Bayesian criteria, numbers of clusters, classification accuracy, prediction accuracy and runtime. Meilă and Heckerman (1998) also found that EM was outperformed in all criteria. However, both EM and CEM are not well-known for sensory studies.

Wajrock *et al*. (2008) compared hierarchical clustering methods (average, Ward's, complete, and single methods) with partitioning methods (k-means, c-means and FANNY), using both collected data and simulated data. Results of actual studies were evaluated for performance indexes of Silhouette, Within/Between, Hubert Gamma, and Dunn, whereas, results of the simulation studies used Hubert and Arabie, Rand, Jaccard, and Fowlkes and Mallows indexes. These indexes measured 1) for actual data criteria, a cluster's compactness and separation; and 2)for simulated data criterion, how similar its clustering is to true clustering results. Results showed partitioning methods outperformed hierarchical methods.

Horn and Huang (2009) used various popular clustering approaches in their research on respondents' life satisfaction: factor segmentation (i.e., factor analysis), k-means clustering (by PROC FASTCLUS in SAS; SAS Institute Inc., Cary, NC, USA), "TwoStep" cluster analysis (by SPSS Inc., Chicago, IL, USA), and latent class cluster analysis (by Latent GOLD 4.5; Statistical Innovations Inc. Belmont, MA, USA). Then the researchers analyzed the respondents' opinions for how satisfied the individuals were with certain aspects of life by rating 29 attributes, e.g., health, faith, social activities, etc. Results yielded different component scores and segmentation solutions; therefore, the clustering approaches yielded different results.

Why Use Cluster Analysis before Preference Mapping

Researchers use cluster analysis together with preference mapping techniques (Liggett *et al.* 2008; Sinesio *et al.* 2010; Schmidt *et al.* 2010). The main purpose of utilizing cluster analysis in acceptability or preference data is to cluster consumers together who have a similar liking pattern, so there will be a more homogenous liking pattern within a cluster (Liggett *et al.* 2008; Wajrock 2008; Sinesio *et al.* 2010; Johanson *et al.* 2010). Thus, consumer liked/disliked products, preference patterns, and product descriptors driving the liking are disclosed and benefit researchers by guiding the direction for development of an ideal product for a specific target consumer segment that is high homogenous in their liking patterns.

Because the product means illustrate different preference patterns in all clusters (though it is not guaranteed), and easiness in performing and calculating the means, researchers are less aware of criticisms about clustering based on a total distance (i.e., hierarchical methods; Meullenet *et al.* 2007). They stated that a researcher can end up "grouping consumers who like some products and disliked others with consumers who dislike all products but dislike some less than others" (Meullenet *et al.* 2007). This resulted in grouping the wrong consumers together into one cluster therefore making clusters that are not homogenous.

To represent product liking within a cluster, product means are calculated, then all cluster vector means are incorporated into the preference map and calculated from either:

a) cluster mean matrix, then create a plot based on only that cluster's mean vectors (Resano *et al.* 2009) or superimposed these vector means in the original preference map with individual consumers (Sinesio *et al.* 2010);
b) merge cluster means into individual consumer overall liking matrix, and create a map using the co-ordinates from this combined matrix (Felberg *et al.* 2010).

In more recent research, Childs and Drake (2009) studied consumer perception of fat reduction cheeses using a survey on 203 and 198 consumers for Cheddar and mozzarella, respectively. They applied Ward's method and Euclidean distances of three to four levels of fat content, flavor, texture and price aspects. Based on the cluster means, two and three distinct clusters were found for Cheddar and mozzarella, respectively.

Resano *et al.* (2009) collected overall acceptability data from 202 consumers on 10 cured ham samples. They performed k-means analysis (with specifying the numbers of cluster based on a dendrogram from Ward's method) and the results showed four clusters. Resano *et al*. plotted an internal preference map based on analysis of the cluster mean matrix.

Felberg *et al.* (2010) used Ward's method and analyzed overall acceptance scores from 60 consumers and 18 prototypes of soy-coffee beverages. Three consumer clusters were found. The acceptance means of clusters were calculated and they illustrated that the samples had significantly different acceptability.

Sinesio *et al.* (2010), using Ward's method, segmented 179 consumers on their overall liking scores of 16 tomato cultivars. Results showed four clusters with different acceptability patterns based on the cluster means.

Conclusions

Is there any disparity in using different preference mapping procedures? Should researchers apply the same method to each consumer segment or to all consumers at once? The answer is likely to be both yes and no. Some researchers may or may not apply one of these methods on each segment of consumers, or they may apply all methods to all consumers at once, depending on the individuals therefore this might be caused by a lack of research that compares the methods of performing the preference mappings. Nevertheless, researchers often prefer to use methods they are more familiar with, or that are easier to access. However, many researchers are not certain which methods are appropriate for their study and may waste valuable time experimenting with different methods.

Comparisons of preference mapping methodologies and consumer segmentation need to be studied further in order to help researchers understand the methods and recognize cautions, therefore researchers receive the most beneficial information (of the chosen method) for their study. Moreover, the outcome of this research will greatly aid product developers by giving them confidence in implementing a preference map. Researchers can use this study as a reference for using preference mapping methodologies and consumer segmentations.

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Chapter 2

CHAPTER 2 - A Comparison of Seven Preference Mapping Techniques Using Four Software Programs

ABSTRACT

Various methods are used to create a preference map based on different theories to model and analyze relationships between product descriptors and consumer preferences. Several programs offer solutions to understand influences and relationships between a descriptive sensory profile and consumer liking, but researchers need to know the (dis)advantages and (dis)similarities of these programs. This study compares the advantages and disadvantages of four statistical software programs and seven multivariate techniques for three empirical studies: milk, paint, and fragrance. Internal and external preference mapping are included in this study. No multivariate method consistently generated a high percent of consumers who mapped closest to their most-liked products. Neither was the variance nor the complete solution explained among descriptors and consumers. For uncomplicated data, researchers can use any method/program to create a preference map when consumer data are highly homogenous in product liking patterns. XLSTAT PLS2 and Unscrambler PLS2 (passified) are recommended for less homogenous consumer data. For complex heterogeneous data, MDPREF is recommended for understanding consumer preference. This study also provides results that indicate the numbers of consumers who map closest to their most-liked products or the preference mean vector are not guaranteed by high percent variance explained in descriptors and/or consumers.

PRACTICAL APPLICATIONS

This research provides information on various types and computer packages for conducting preference mapping studies. Results from the study show that when the interpretation of maps is implemented without further analysis, preference maps can be misleading, and thus, may be overused.

INTRODUCTION

Preference mapping is a graphical display created by multivariate analysis methods. Preference maps plot product co-ordinate component scores versus consumers and/or attribute vectors derived through the distances of data matrices in geometric space. This is used to help researchers understand influences of attributes on consumer liking (Michon *et al*. 2010; Sinesio *et al*. 2010), differences among products (Villanueva *et al*. 2009; Felberg *et al*. 2010), and segments of products and consumers (Sveinsdóttir *et al*. 2009; Oupadissakoon *et al.* 2010). Researchers also use preference maps, along with liking scores, for guidance in predicting new prototypes; the most popular types being internal and external preference mapping. Chang and Carroll (1969) developed internal preference mapping (MDPREF) to perform principal component analysis (PCA) on consumer liking data and create preference plot(s) for the first few component values.

External preference mapping is a dimension reduction multivariate method performed on sensory data, followed by regressing consumer liking data onto the first two components. Though more components can be used, it is typical for a preference map to be based on the first two components. This is conducted using the PCA on a matrix of descriptor means and by adding a column of consumer preference means into the matrix (Felberg *et al*. 2010; Sinesio *et al*. 2010).

The original PREFMAP was developed from Carroll (1972) who created a preference map based on multidimensional scaling and an unfolding model. Meulman *et al.* (1986) adapted PREFMAP by regressing consumer preferences onto a vector model using PCA, and ideal point (or unfolding), weighted unfolding and general unfolding models using multidimensional scaling. Schlich (1995) used PCA to reduce the descriptive sensory dimensions. Then the PCA component scores from individual consumers were regressed through a vector, circular, elliptical, or quadratic model. The individual vectors or ideal points could be represented in a map. This method also is called PREFMAP (Schlich 1995; Carbonell *et al*. 2008). Canonical variate analysis (Hein *et al.* 2009) and generalized procrustes analysis (Nestrud and Lawless 2008) perform a dimension reduction allowing consumer preferences to be regressed on their component scores creating an external preference map. A variation of PCA techniques, partial least square regression (PLS), is used to create preference maps (Sveinsdóttir *et al*. 2009; Michon *et al*. 2010) by regressing both descriptive sensory data and consumer liking data. The PLS seeks common components that "perform simultaneous decomposition" (Martens and Martens 2001) of a descriptive attribute and consumer liking matrix to maximize the covariance between those two matrices. Whereas, PCA components focus only on maximizing the variance explained in a descriptive attribute matrix. The common types of PLS used in sensory studies are PLS1 (one of the two data matrices is a single column of mean liking scores), and PLS2 (both data matrices are multidimensional; Rosipal and Krämer 2006; Tang *et al*. 2000).

These various statistical techniques are offered by numerous software programs. While researchers expect that any software and method uses will yield similar outputs and interpretations, they may not be aware that original output, co-ordinate values on the map, and predictive equations are dissimilar. What happens if we take values from the map for further analysis and calculation? Knowing how diverse methodologies and software may produce distinctions in the maps could make output and interpretation more reliable.

Using a statistical point of view, Williams *et al*. (1988) compared GPA against PLS. The results found that GPA yielded a more reliable map for a free choice profile method while PLS generated a more meaningful interpretation, because PLS incorporated a variation of both descriptive and consumer data. Hunter and Muir (1995) created preference maps by implementing GPA and PCA. They suggested that GPA plots differentiated samples in a better way by looking at the variance ratios. The standard errors of GPA were smaller, although it tended to require more components than PCA in some situations. Rougoor *et al*. (2000) and Adnan *et al*. (2006) stated that PLS handles multi-collinearity problems with a slightly more effective outcome than PCR. In the sensory field, Chung *et al*. (2003) correlated descriptive sensory data to chemical data using GPA and PLS. The conclusion was that both methods were effective, except that PLS yielded a non-meaningful plot when calculated from log-transformed data. Van Keef *et al*. (2006) explored internal versus external preference analysis on end-user evaluation. They stated that internal analysis was sufficient for marketing, and external analysis was adequate for food technologists to optimize ingredients, thus the interface of marketing and technologists would need both analyses. Researchers need to know the advantages, disadvantages, and (dis)similarities of various software packages, because many statistical techniques perform dimension reduction to create preference maps. Then researchers can interpret the maps produced by different methods and software to decide which method and software should be used in their research. The objective of this study is to compare various outputs, advantages, and disadvantages of methods and software programs, to assist sensory scientists in choosing the preference mapping method best suited for their research.

MATERIALS AND METHODS

Empirical data from three studies: milk (Adhikari *et al*. 2010), paint, and fragrance (Retiveau 2004), containing both consumer and descriptive data were evaluated using seven multivariate techniques. These studies varied by number of samples, consumers, sensory descriptors, and data variability (Supplementary results for chapter 2A).

The three studies represent various levels of complexity based on consumer results. In the paint study, data was clear and consistent. The overall acceptance data clearly showed almost all consumers scored one product (399) highest and 3 products (290, 209, and 116) lowest of the 10 paints studied. In the milk study, six products were tested and consumers generally gave one product (REG3) the highest and one product (LFA0) the lowest overall liking scores, but there were some small differences in liking for some consumers (Adhikari *et al*. 2010). The fragrance study was a complex study with 22 samples and heterogeneous product liking and disliking. For example, consumers gave multiple products (621, 517, 237, 638, and 211) the highest scores and one product (412) the lowest scores for liking (Retiveau 2004). Individual consumer segments also liked different ones of the five top rated products.

Different number of samples, consumers, and types of products were used in both descriptive and consumer studies (Table 2.1A and B). Four statistical software programs, SAS (version 9.2, SAS Institute, Cary, NC, USA), Unscrambler (version 9.7,

TABLE 2.1 CHARACTERISTICS OF THE MILK, PAINT, AND FRAGRANCE DATA

(A) CONSUMER DATA DESCRIPTION

Consumer studies	Samples	Consumers	Scales	Skewness	Overall STDs	Range of STDs	Range of sample means
Milk	6	115	1-9[a]	Skewed to left	2.2	1.5-2.3	4.3-6.9
Paint	10	98	1-9[a]	Skewed to left	2.4	1.7-2.4	3.6-7.6
Fragrance	22	321	1-7[b]	Skewed to left	1.8	1.5-1.9	3.1-5.3

STD represents standard deviation
[a] 9-point hedonic scale: 1 = dislike extremely; 2 = dislike very much; 3 = dislike moderately; 4 = dislike slightly; 5 = neither like nor dislike; 6 = like slightly; 7 = like moderately; 8 = like very much; 9 = like extremely.
[b] 7-point hedonic scale: 1 = dislike very much; 2 = dislike moderately; 3 = dislike slightly; 4 = neither like nor dislike; 5 = like slightly; 6 = like moderately; 7=like very much.

(B) DESCRIPTIVE DATA DESCRIPTION

Descriptive studies	Samples	Trained panelists	Scales (none - extreme)	Descriptors	Range of STDs	Range of sample means
Milk	6	7	0-15, with 0.5 increments	21	0.3-2.4	0.2-3.1
Paint	10	6	0-15, with 1.0 increments	6	na	8.5-12.5
Fragrance	22	7	0-15, with 0.5 increments	56	0.2-1.3	0.1-4.6

STD represents standard deviation
na represents not applicable.

CAMO Software Inc., Woodbridge, NJ, USA), XLSTAT (version 2010, Addinsoft, New York, NY, USA), and Senstools (version 3.1.4, OP&P Product Research BV, Utrecht, The Netherlands), seven multivariate techniques, and some variants (if applicable) were used for the analysis:

1) SAS[1] MDPREF, PROC FACTOR
2) SAS[1] PCA, PROC FACTOR, with a mean liking score column incorporated into descriptive data matrix.
3) SAS[1] modified-PREFMAP[2]
4) SAS[1,3] CVA, PROC DISCRIM
5) XLSTAT[3] GPA
6) Senstools[3] GPA
7) SAS[3] PLS1, PROC PLS
8) XLSTAT[4] PLS1, PROC PLS
9) Unscrambler[4] PLS1
10) Unscrambler[4] PLS1 passified
11) SAS[1] PLS2, PROC PLS
12) XLSTAT[4] PLS2
13) Unscrambler[4] PLS2
14) Unscrambler[4] PLS2 passified

All products, consumer (individual or vector) and descriptive attribute co-ordinates, were transferred to Excel 2007 for construction of the final maps.

For the paint study, descriptive panel consensus data was used making the CVA and GPA not applicable to this study because these techniques require replicated descriptive data.

For the fragrance study, the XLSTAT PLS1 did not apply because it gave only one component, thus making it impossible to create a preference map. This was

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[1] The co-ordinates were minimized or maximized within ±1 making them comparable to one another.
[2] This modified-PREFMAP regresses consumers using vector, circular, and elliptical models with representation of individual vectors in the displays.
[3] After extracting the components, consumer liking scores were regressed onto the first 2 components using an AUTOFIT strategy (Schlich, 1995).
[4] The co-ordinates used were the original co-ordinates.

confirmed by the manufacturer of the software who conducted their own analysis and concluded that a second component would not benefit the model for this particular data set. All preference maps compared the following: co-ordinate values, variance explained on the first two components, consumer space, descriptive space, attributes that promote liking, closeness of consumers to their most liked products, and advantages or disadvantages. The distance between individual consumer co-ordinates closest to its most-liked product was measured in Euclidean space.

RESULTS AND DISCUSSION

Map Configuration

The nature of a method dictates some inherent differences in the results. For example, PCA and PLS1 map (Fig. 2.1) use mean acceptance data and, thus showed only the position of mean acceptance for all consumers taken together as one single group. MDPREF, PLS2, and modified-PREFMAP (Fig. 2.1 and 2.2) provided more detail on the distribution of individual preferences and attributes that appear to promote liking, as well as product characteristics. MDPREF exhibits the acceptance pattern of each individual consumer, but does not show descriptive sensory information. PLS2 and modified-PREFMAP provide information on descriptive attributes, which is similar to PCA, but shows the individual consumers' positioning on the map instead of mean liking for the consumers as shown in the PCA.

Coordinate Values

Different techniques yield unequal co-ordinate values (Table 2.2A-C). Different software yields dissimilar and smaller values in (un)passified PLS1, (un)passified PLS2, and GPA. Those may be caused by using certain software that applied a distinct calculation formula in positioning the co-ordinates in their plots.

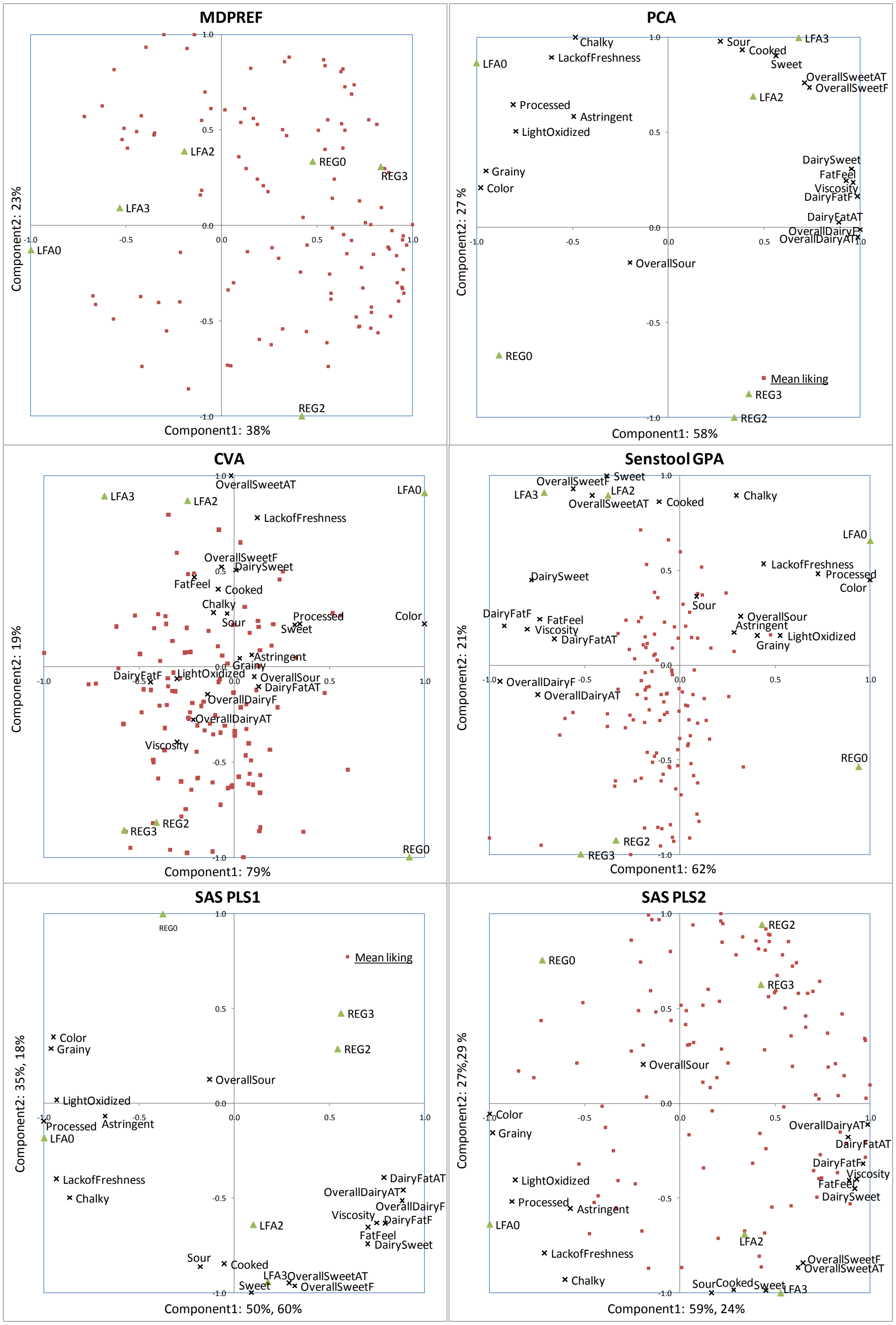

FIG. 2.1 A BIPLOTS OF PRODUCTS SCORES, DESCRIPTIVE VARIABLE LOADINGS, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FROM (PARTIAL) DIFFERENT PREFERENCE MAPPING TECHNIQUES USED FOR MILK STUDY ON COMPONENTS 1 AND 2

(FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour)

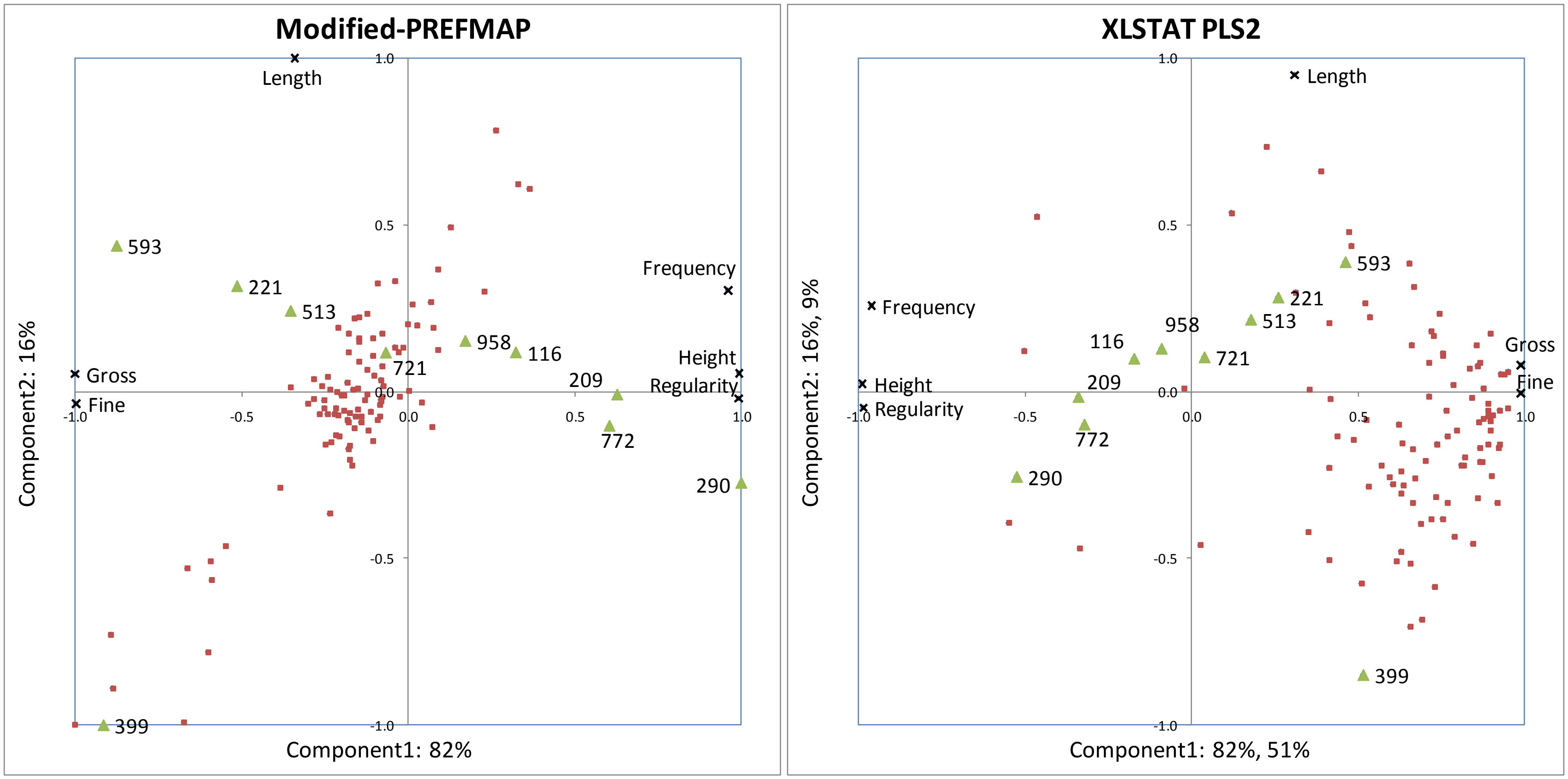

FIG. 2.2 BIPLOTS OF PRODUCTS SCORES, DESCRIPTIVE VARIABLE LOADINGS, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FROM (PARTIAL) DIFFERENT PREFERENCE MAPPING TECHNIQUES USED FOR PAINT STUDY ON COMPONENTS 1 AND 2
(Gross = Gross image, Fine = Fine image, Length = Wave length, Height = Wave height, Frequency = Wave frequency, Regularity = Wave regularity)

Variance Explained on the First 2 Components

The percentage of variance explained in the descriptive attributes and consumers differed among the multivariate techniques. (Among the descriptive attributes, Table 2.3 illustrates the percent variance explained for the milk study using PCA, modified-PREFMAP, XLSTAT GPA, CVA and PLS2 for Component 1 and 2; the results were 85, 96, 84, 89, and 86 percent explained variance among descriptors, respectively. Fluctuation in percentage also was found in Moussaoui and Varela (2010), Nestrud *et al*. (2008), and Sveinsdóttir *et al*. (2009). Across software programs, percentages did not shift for PLS1, PLS2, and were almost equal for GPA. For example, PLS1 calculated 85% for percentage of variance explained when using SAS, XLSTAT, and Unscrambler (either passified or unpassified).

Although it could be argued that the basis of the multivariate methods is different, comparisons therefore, may be inappropriate because: 1) MDPREF is calculated based on consumer data only, 2) PCA and PLS1 used all consumer data as a single mean vector, 3) AUTOFIT together with modified-PREFMAP, GPA, and CVA took into account only consumers validated to best fit the vector model, and 4) PLS2 weighted all consumers equally. It is also reasonable to believe that a considerably higher percent variance explained would indicate a better method. Table 2.3 illustrates the percent variance explained for the milk study calculated by PCA, modified-PREFMAP, Senstools GPA, CVA and PLS2 with the results being 78, 73, 81, 85, and 53, respectively. This data, by itself seems to indicate that the PLS2 is not as explanatory as the other techniques when based on only Components 1 and 2. However, other data must also be considered.

Across software programs, percentages do not shift for PLS1 and are essentially the same across GPA (shift within ±3%) and PLS2 (shift within ±1%) programs (Table 2.3). For example, the percentages are 53, 54, 53, and 53 when calculated via SAS, XLSTAT, and Unscrambler (either passified or unpassified), respectively.

If percent variance explained for both the descriptive attributes and consumers is high (i.e., 98% and 94% respectively, in the paint study), then applying any method/program(s) used in this study will yield the same results.

TABLE 2.2 PREFERENCE MAPS' CO-ORDINATE VALUES

(A) PARTIAL COORDINATES OF DESCRIPTIVE ATTRIBUTES, SAMPLES, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FOR MILK STUDY ON COMPONENTS 1 AND 2

Method	Component	Descriptive attributes				Mean liking	Products		Consumer			
		Color	Chalky	Fat feel	Viscosity		LFA0	LFA2	C1	C2	C3	C4
MDPREF	1						-1.000	-0.195	1.000	0.723	-0.625	-0.422
	2						-0.128	0.390	0.003	-0.529	0.626	0.575
PCA	1	-0.979	-0.485	0.929	0.965	0.497	-1.000	0.442				
	2	0.209	1.000	0.245	0.237	-0.792	0.864	0.688				
Modified-PREFMAP	1	-0.993	-0.506	0.939	0.952		-1.000	0.367	0.161	0.278	0.074	0.260
	2	0.172	1.000	0.317	0.260		1.000	0.743	-0.908	-0.435	0.711	0.564
CVA	1	1.000	-0.109	-0.211	-0.300		1.000	-0.246	-0.248	-0.367	-0.081	-0.301
	2	0.223	0.284	0.468	-0.395		0.911	0.870	-0.976	-0.437	0.717	0.595
SAS PLS1	1	-0.950	-0.865	0.703	0.748	0.596	-1.000	0.099				
	2	0.349	-0.498	-0.655	-0.633	0.772	-0.182	-0.640				
XLSTAT PLS1	1	-0.930	-0.847	0.688	0.732	0.772	-0.819	0.081				
	2	0.339	-0.484	-0.636	-0.615	0.419	-0.123	-0.432				
Unscrambler PLS1	1	-0.930	-0.847	0.688	0.732	0.772	-1.000	0.099				
	2	0.339	-0.484	-0.636	-0.615	0.419	-0.182	-0.640				
Unscrambler PLS1	1	-0.930	-0.847	0.688	0.732	0.772	-0.819	0.081				
(passified)	2	0.339	-0.484	-0.636	-0.615	0.419	-0.123	-0.432				
SAS PLS2	1	-1.000	-0.603	0.889	0.930		-1.000	0.339	0.331	0.735	0.009	0.416
	2	-0.056	-0.930	-0.406	-0.400		-0.637	-0.691	0.879	0.643	-0.868	-0.807
XLSTAT PLS2	1	-0.987	-0.595	0.878	0.918		-0.725	0.246	0.308	0.685	0.008	0.388
	2	-0.048	-0.795	-0.348	-0.343		-0.361	-0.391	0.854	0.624	-0.843	-0.784
Unscrambler PLS2	1	-0.987	-0.595	0.878	0.918		-1.000	0.339	0.308	0.685	0.008	0.388
	2	-0.048	-0.795	-0.348	-0.343		-0.637	-0.691	0.854	0.624	-0.843	-0.784
Unscrambler PLS2	1	-0.987	-0.595	0.878	0.918		-0.725	0.246	0.308	0.685	0.008	0.388
(passified)	2	-0.048	-0.795	-0.348	-0.343		-0.361	-0.391	0.854	0.624	-0.843	-0.784
Senstools GPA	1	1.000	0.297	-0.736	-0.802		1.000	-0.377	-0.101	-0.171	-0.061	-0.175
	2	0.448	0.897	0.241	0.190		0.657	0.896	-0.955	-0.460	0.660	0.529
XLSTAT GPA	1	0.987	0.485	-0.946	-0.966		1.000	-0.379	-0.101	-0.172	-0.062	-0.178
	2	0.203	0.945	0.210	0.254		0.661	0.894	-0.954	-0.460	0.660	0.529

(B) PARTIAL COORDINATES OF DESCRIPTIVE ATTRIBUTES, SAMPLES, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FOR PAINT STUDY ON COMPONENTS 1 AND 2

Method	Component	Descriptive attributes				Mean acceptabilty	Products		Consumer			
		Gross image	Fine image	Wave frequency	Wave regularity		209	399	C1	C2	C3	C4
MDPREF	1						-0.459	1.000	0.502	0.556	0.984	0.861
	2						0.085	0.075	0.524	-0.999	-0.185	-0.370
PCA	1	0.999	1.000	-0.971	-0.989	0.976	-0.654	1.000				
	2	0.085	-0.005	0.270	-0.059	-0.170	-0.023	-1.000				
Modified-PREFMAP	1	-1.000	-0.997	0.960	0.993		0.627	-0.915	-0.123	0.127	-0.210	-0.092
	2	0.053	-0.036	0.304	-0.021		-0.008	-1.000	0.065	0.493	0.192	0.325
SAS PLS1	1	1.000	1.000	-0.972	-0.996	0.916	-0.648	0.985				
	2	-0.083	0.008	-0.269	0.061	0.941	0.031	1.000				
XLSTAT PLS1	1	0.989	0.989	-0.962	-0.985	0.953	-0.340	0.517				
	2	-0.080	0.007	-0.255	0.058	0.162	0.024	0.845				
Unscrambler PLS1	1	0.989	0.989	-0.962	-0.985	0.953	-0.649	0.986				
	2	-0.080	0.007	-0.255	0.058	0.162	0.029	1.000				
Unscrambler PLS1	1	0.989	0.989	-0.962	-0.985	0.953	-0.340	0.517				
(passified)	2	-0.080	0.007	-0.255	0.058	0.162	0.024	0.845				
SAS PLS2	1	1.000	1.000	-0.971	-0.996		-0.647	0.980	0.548	0.436	0.972	0.807
	2	0.084	-0.005	0.271	-0.052		-0.018	-1.000	0.360	0.278	-0.077	-0.186
XLSTAT PLS2	1	0.989	0.989	-0.961	-0.986		-0.340	0.515	0.521	0.415	0.925	0.768
	2	0.079	-0.005	0.258	-0.049		-0.016	-0.849	0.264	0.204	-0.056	-0.136
Unscrambler PLS2	1	-0.989	-0.989	0.961	0.986		0.647	-0.980	-0.521	-0.415	-0.925	-0.768
	2	0.079	-0.005	0.258	-0.049		-0.018	-1.000	0.264	0.204	-0.056	-0.136
Unscrambler PLS2	1	-0.989	-0.989	0.961	0.986		0.340	-0.515	-0.521	-0.415	-0.925	-0.768
(passified)	2	0.079	-0.005	0.258	-0.049		-0.016	-0.849	0.264	0.204	-0.056	-0.136

(C) PARTIAL COORDINATES OF DESCRIPTIVE ATTRIBUTES, SAMPLES, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FOR FRAGRANCE STUDY ON COMPONENTS 1 AND 2

Method	Component	Descriptive attributes				Mean liking	Products		Consumer			
		Strength	Solvent	Lemon	Bergamot		517	621	C1	C2	C3	C4
MDPREF	1						0.56	0.50	0.29	0.53	0.04	0.40
	2						0.33	0.85	0.68	-0.46	0.30	-0.01
PCA	1	0.27	0.94	-0.25	0.81	0.08	0.41	-0.83				
	2	0.72	0.24	-0.80	0.24	0.45	0.02	-0.10				
Modified-PREFMAP	1	0.24	-0.66	-0.11	-0.62		-0.46	1.00	0.78	0.04	0.24	0.27
	2	0.99	0.69	-0.84	0.57		0.19	-0.61	-0.76	0.58	-0.11	0.18
CVA	1	0.19	-0.02	0.05	-0.04		-0.06	0.67	0.50	0.16	0.35	0.30
	2	0.61	0.17	-0.15	0.13		0.33	-0.84	-0.79	0.48	0.06	0.11
SAS PLS1	1	0.72	0.50	-0.57	0.62	0.53	0.29	-0.04				
	2	-0.55	-0.45	1.00	-0.30	0.83	0.37	0.92				
Unscrambler PLS1	1	0.47	0.33	-0.37	0.41	0.73	0.29	-0.04				
	2	-0.36	-0.29	0.65	-0.20	0.55	0.37	0.92				
Unscrambler PLS1 (passified)	1	0.47	0.33	-0.37	0.41	0.73	0.17	-0.02				
	2	-0.36	-0.29	0.65	-0.20	0.55	0.15	0.37				
SAS PLS2	1	-0.58	-0.91	0.60	-0.81		-0.43	0.83	0.51	0.38	0.23	-0.43
	2	0.37	-0.34	-0.42	-0.25		-0.09	0.28	0.39	-0.02	0.05	-0.21
XLSTAT PLS2	1	-0.48	-0.76	0.50	-0.67		-0.17	0.33	0.39	-0.40	0.25	-0.03
	2	0.31	-0.29	-0.35	-0.21		-0.06	0.18	0.29	0.29	0.20	0.29
Unscrambler PLS2	1	0.48	0.76	-0.50	0.67		0.43	-0.83	-0.39	0.40	-0.25	0.03
	2	0.31	-0.29	-0.35	-0.21		-0.09	0.28	0.29	0.30	0.21	0.29
Unscrambler PLS2 (passified)	1	0.48	0.76	-0.50	0.67		0.17	-0.33	-0.39	0.40	-0.25	0.03
	2	0.31	-0.29	-0.35	-0.21		-0.06	0.18	0.29	0.30	0.21	0.29
Senstools GPA	1	-0.24	0.64	0.15	0.53		0.47	-1.00	-0.78	-0.03	-0.32	-0.28
	2	1.00	0.58	-0.63	0.58		0.21	-0.61	-0.68	0.59	-0.11	0.19
XLSTAT GPA	1	0.23	-0.67	-0.11	-0.64		-0.46	1.00	0.78	0.03	0.32	0.28
	2	-0.98	-0.69	0.83	-0.57		-0.21	0.61	0.68	-0.59	0.11	-0.19

TABLE 2.3 PERCENTAGES REPRESENTING VECTOR(S) CLOSEST TO MOST-LIKED PRODUCTS, VARIANCE EXPLAINED AMONG DESCRIPTIVE ATTRIBUTES AND THAT AMONG CONSUMERS

Method	%								
	Milk study			Paint study			Fragrance Study		
	Number of consumers who map closest to their most-liked products	Variance explained in descriptive attributes	Variance explained in consumers	Number of consumers who map closest to their most-liked products	Variance explained in descriptive attributes	Variance explained in consumers	Number of consumers who map closest to their most-liked products	Variance explained in descriptive attributes	Variance explained in consumers
MDPREF	56	na	61	55	na	67	32	na	29
PCA	REG3*	85**		593*	98**		513*	44**	
SAS PLS1	REG3*	85	78	399*	98	95	237*	26	83
XLSTAT PLS1	REG3*	85	78	593*	98	94	na	na	na
Unscrambler PLS1	REG3*	85	78	593*	98	94	237*	26	83
Unscrambler PLS1 (passified)	REG3*	85	78	593*	98	94	237*	26	83
Modified-PREFMAP	46	96	73	15	98	62	27	61	72
Senstools GPA	42	83	81	na	na	na	26	52	80
XLSTAT GPA	43	84	78	na	na	na	26	52	78
CVA	42	89	85	na	na	na	26	40	74
SAS PLS2	55	86	53	56	98	60	22	44	17
XLSTAT PLS2	55	86	54	68	98	60	27	45	17
Unscrambler PLS2	56	86	53	44	98	60	25	45	17
Unscrambler PLS2 (passified)	55	86	53	68	98	60	27	45	17

* Sample name or sample code that a consumer mean liking vector is located closer to.
** The percent variance explained both descriptive attributes and consumers that calculated from a matrix of descriptors' means with an additional column of consumer preference mean.
na = not applicable.

Consumer Space

Consumer positions in all maps were diverse (Table 2.2A-C; Supplementary results for chapter 2B-E). MDPREF (Figs. 2.1 and 2; Supplementary results for chapter 2C-E) indicates only which products were liked/not-liked in relation to specific consumers, whereas, the PCA map showed what products correlated highly with the average liking score vector and the characteristics of the liked products. Modified-PREFMAP, CVA, and GPA used AUTOFIT to validate each consumer to best fit one of three mathematical models, i.e., vector, circular, and elliptical models. No published studies in sensory research were found for a modified-PREFMAP display that had a specific model to best fit individual consumers in the plot. When all consumers are incorporated on this map there can be a problem because consumers who are the best fit for non-vector models are disconnected. Therefore, visually showing a preference map based on only one vector model, but retaining consumers on the map who best fit circular or elliptical models may be misleading. MDPREF, PLS1 and PLS2 produced a map of descriptive attributes explaining the variation of all consumers; meaning researchers can draw conclusions based on total data, not just a portion (as in AUTOFIT), but often the variance explained for consumers is low. In modified-PREFMAP, PLS1 and PLS2, individual consumers are modeled using the descriptive data. PLS1's liking vector, based on mean liking scores, was always placed in the same upper right quadrant. Because PLS1 uses the mean vector, maps may not represent what individual consumers actually like.

Descriptive Space

Among all external preference maps, the interpretations of attribute positions relative to product positions were similar when the maps had a high percentage of variance explained in descriptive attributes, such as with the milk study (Supplementary results for chapter 2C). With 86% average variance explained among the descriptors, all maps in the milk study (Fig. 2.1) illustrate LFA0 and REG0 have less fatty-attributes, and more "light oxidized and lack of freshness" attributes. Opposite those two samples are REG3 and LFA3, which have more fatty-rated attributes, and less "light oxidized and lack of freshness" attributes. Configurations from all methods and software programs in the paint study were similar with 98% variance explained among the descriptors. Therefore, only the maps from modified-PREFMAP and XLSTAT PLS2 are presented. Sample 116, 209 and 290 have more wave height, frequency, and regularity, and less gross image attributes (Fig. 2.2).

The fragrance study (Table 2.3) had lower (42%) variance explained among the descriptors (averaged over all multivariate methods, range: 26-61%) than the other studies. Product 517 is more oriental woody in 10 of 14 maps [all except CVA (Fig. 2.3), SAS PLS1, Unscrambler PLS1, and Unscrambler PLS2, passified]. Product 492 had high strength and white flower attributes in nine of 14 maps (all except CVA and all PLS1 analyses). When there is a lower percent variance explained among the descriptors, together with complexity of samples and consumers, such as in the fragrance study, the preference map can begin to be misleading.

Attributes that Promote Liking

When the maps (Supplementary results for chapter 2C and D) had a high percentage of variance explained in descriptive attributes (> 83%), methods used in this study suggested similar attributes that promote liking/acceptability. It was difficult to specify attributes that promote liking when the maps (Supplementary results for chapter 2E) had low percentages and contained individual consumers because the maps were visually crowded.

Closeness of Consumers to Their Most Liked Products

Unlike internal preference mapping, all external preference mapping procedures initially place descriptive sensory attributes and product co-ordinates based on the descriptive sensory data rather than the consumer data. This does not guarantee that consumers would be positioned close to their most-liked products, nor does it assure that the mean preference vector will be positioned close to the most-liked products. Therefore, being aware of how close individual consumer positions were to their most-liked products in a preference map can help researchers understand and use findings in the map with confidence. Distances between individual consumers and their most-liked products were compared by measuring Euclidean distance. Table 2.3 indicates MDPREF and PLS2 (from any program) equally yielded 56% of consumers who map closest to their most-liked products for the milk study. For the paint study, XLSTAT and Unscrambler (passified) PLS2 yielded the highest value of 68% of consumers who map closest to their most-liked products. MDPREF yielded the highest value at 32% of consumers who map closest to their most-liked products for the fragrance study. All other methods/programs resulted in even lower percentages of consumers who map closest to their most like products for the fragrance study. This occurred because the fragrance study had many samples, descriptive attributes, subgroups of consumer preferences, and contained many most-liked and most-disliked products.

Among the 3 data sets, the techniques that use average liking scores (PCA, XLSTAT PLS1, Unscrambler PLS1, and Unscrambler PLS2 passified) can fail when positioning consumer mean preference coordinates close to products with the highest mean-liking score. This means those preference maps are potentially misleading when trying to understand liking vectors visually.

Advantages and Disadvantages

The advantages and disadvantages of implementing software programs and multivariate techniques are summarized in Table 2.4; favoritism was avoided. Researchers can use this information to choose what is best for their individual research.

In general, product configuration was calculated based on consumer data for MDPREF, descriptive sensory data for modified-PREFMAP, CVA and GPA, and both consumer and descriptive sensory data for PLS1 and PLS2. PLS1 and PLS2 provide a contribution of consumer data to the map configuration. However, the percent variance explained among consumers could be about half of MDPREF's results (see fragrance study, Table 2.3 and Fig. 2.3). Moreover, the best explanation of consumer preference may come from components other than 1 and 2, but Component 1 and 2 were MDPREF's strong points (Greenhoff and MacFie 1994; van Kleef *et al*. 2006).

PCA, XLSTAT PLS1, and Unscrambler PLS1 have a higher chance of mis-locating the mean liking vector to its highest-average-liking-score product than

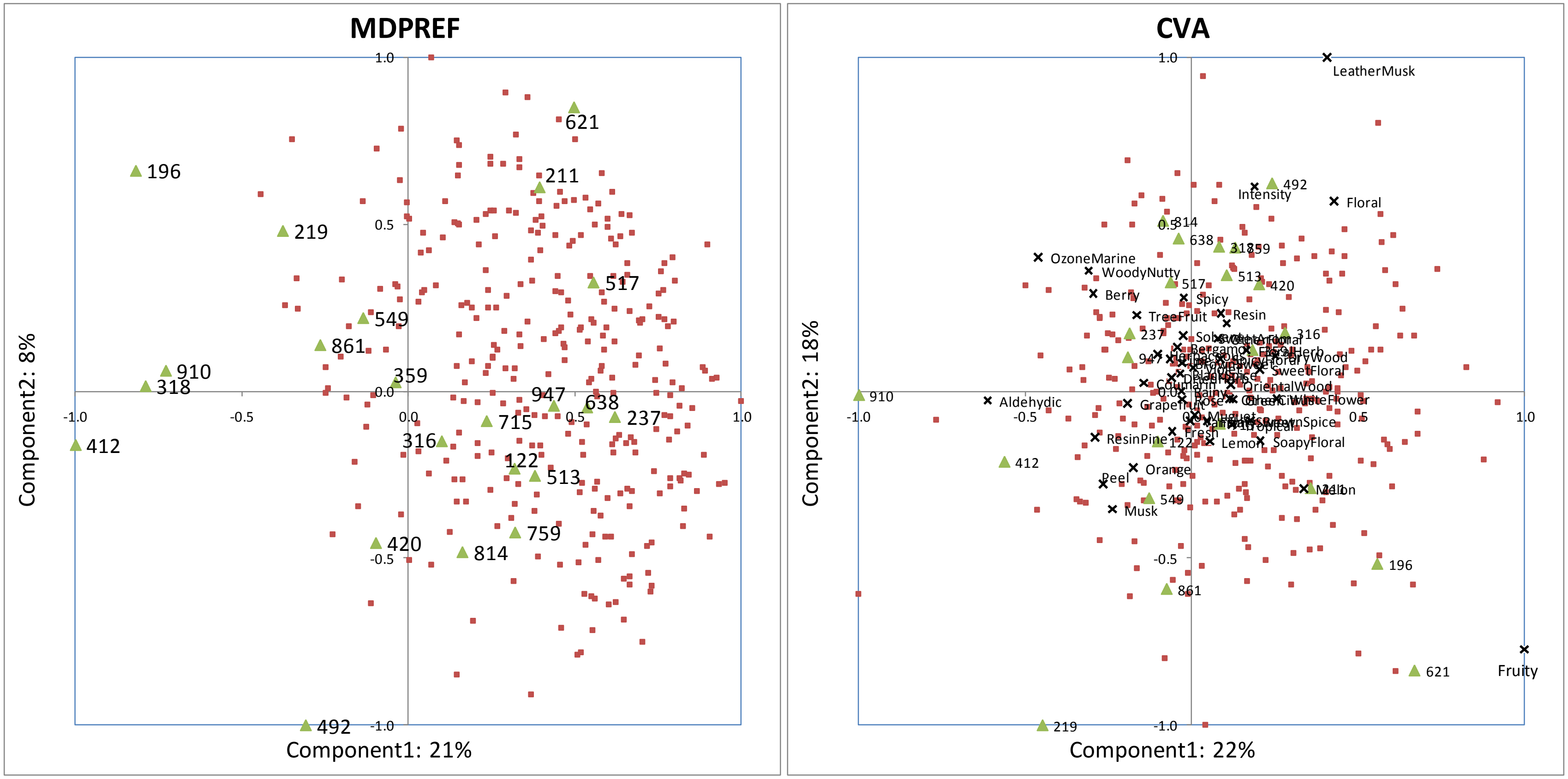

FIG. 2.3 BIPLOTS OF PRODUCTS SCORES, DESCRIPTIVE VARIABLE LOADINGS, AND CONSUMER-MEAN-LIKING VECTOR/INDIVIDUAL CONSUMERS' VECTORS FROM (PARTIAL) DIFFERENT PREFERENCE MAPPING TECHNIQUES USED FOR FRAGRANCE STUDY ON COMPONENTS 1 AND 2

SAS PLS1, and these maps also suggest only one ideal product to satisfy all consumers. Whereas, CVA and GPA crowded all vectors together making maps hard to interpret.

Van Kleef *et al*. (2006) also suggested that although MDPREF clearly benefits marketing and product creativity, external preference maps were more actionable for product developers. No preference map technique would be superior to any other for the interface of marketing and product development.

TABLE 2.4 ADVANTAGES AND DISADVANTAGES OF DIFFERENT PREFERENCE MAPPING METHODS USED IN THIS STUDY

Method	Pros	Cons
MDPREF	▪ Highest number of consumers who map close to their most-liked products ▪ Only method with product spatial calculated on consumer hedonic scores (Jaeger *et al*. 2000); however, the product space is different from the other methods ▪ Simple to perform and interpretation is clear ▪ Helps locate a new possible market (McEwan 1996) ▪ Shows the attributes that must be changed to alter a product position (McEwan 1996)	▪ Not easy to overlay with the descriptive spatial. ▪ Difficult to identify the most-liked product when consumers do not agree on a most-liked product ▪ The variation of data explained by each component is often low (McEwan 1996)
PCA	▪ Higher chance of mis-locating the mean liking vector to its highest-average-liking-score product ▪ Incorporates the coordinate of the average consumers' liking score vector so it indicates where the satisfied product of this group of consumer is located. ▪ Simple to perform, but interpretation is not clear	▪ Coordinate of the average liking score vector is not necessarily correct ▪ When products differ greatly, results show in less than 50% variance explained; i.e., map not very helpful
Modified-PREFMAP	▪ With about 115 consumers and 10 samples, maps are well spread, and easy to read; however, maps are crowded with 321 consumers and 22 samples ▪ Remains the same products and attribute oriented as PCA with showing consumers spatial ▪ Shows positions of individual consumers	▪ Requires familiarity with SAS

CVA	▪ Shows the map at a different angle ▪ Shows positions of individual consumers	▪ When data contains many samples, descriptive attributes, and consumers, they tend to crowd together ▪ Requires replication for descriptive sensory study
PLS1 (in general)	▪ Easier to identify drivers of liking	▪ Coordinate of an average liking score vector, generated by Unscrambler and XLSTAT, is not necessarily correct, e.g., in paint study, the vector was located near 593 instead of 399 (Table 2.3) ▪ Suggests only one prototype that balances the intensity across all descriptive attributes to satisfy all consumers. Assumes the relationship between liking and sensory intensity for a given attribute is linear (Meullenet *et al*. 2007)
SAS PLS1	▪ Better in positioning the mean liking vector closer to products that were higher in their liking scores than XLSTAT PLS1, Unscrambler (with and without passified) PLS1, and PCA ▪ All coordinates are well spread ▪ Easier to spot errors in the data/process ▪ Provides actual values if needed to formulate a predictive equation	▪ A challenging procedure; in addition to needing the ability to use SAS language, this requires background knowledge
XLSTAT PLS1	▪ Better chance than PCA in locating a mean liking vector closer to the high-liking scored products ▪ Yields a symmetry map	▪ May not create a map (while other programs do) because of how the original data is configured ▪ The descriptive data of each trained panelist must be arranged by width instead of length; risk running out of columns if not using Excel 2007 ▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this
Unscrambler PLS1	▪ Better chance than PCA in locating a mean liking vector closer to the high-liking scored products	▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this ▪ Maps are distorted

Unscrambler PLS1 passified	▪ Better chance than PCA in locating a mean liking vector closer to most high-liking scored products ▪ Effortless to get the final map	▪ Tends to narrow the spatial of products, making the map very crowded in the middle ▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this ▪ Maps are distorted
PLS2 (in general)	▪ Shows where each consumer is and helps identify different groups of consumer preference; aids in positioning prototypes ▪ Difficult to define drivers of liking ▪ Presents high number of consumer coordinates near their most-liked products as with MDPREF	▪ Coordinates widely spread when consumers do not agree
SAS PLS2	▪ Similar to Unscrambler PLS2 for spatial wise.	▪ A challenging procedure; in addition to needing the ability to use SAS language, this program requires background knowledge
XLSTAT PLS2	▪ Coordinates values similar to Unscrambler PLS2 passified ▪ Yields a symmetry map	▪ Tends to narrow the spatial of products ▪ The descriptive data of each trained panelist must be arranged by width instead of length; risk running out of column if not using Excel 2007 ▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this
Unscrambler PLS2	▪ Similar to Unscrambler PLS2 for spatial of samples, descriptive attributes, and individual consumers.	▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this ▪ Maps are distorted
Unscrambler PLS2 passified	▪ Coordinates values similar to XLSTAT PLS2 passified	▪ Extra steps programmers add to the process of creating a map may not be obvious; users may be unaware of this ▪ Unscambler's maps are distorted
GPA (in general)	▪ Spatially similar to XLSTAT and Senstools maps ▪ XLSTAT and Senstools represent consumers who map closest to their most-liked products in the same distance ratio ▪ Equal in values of consumer and product coordinates	▪ Fewer consumers who map close to their most-liked products ▪ Maps from averaged values in XLSTAT/Senstools programs are clearer than maps manually calculated from averaged values because the program map tends to stretch the attribute space ▪ Replications required in descriptive studies

Senstools GPA	▪ Map is symmetric ▪ Sometime calculated values of the program itself do not equal those of manual calculation ▪ Spatially similar for product, attribute, and consumer space.	
XLSTAT GPA	▪ Map is symmetric ▪ Calculated values of the program itself equal manual calculation ▪ Spatially similar for product, attribute, and consumer spaces.	

DISCUSSION

All preference maps in this study have product co-ordinates plotted based on the descriptive sensory data, not on consumer data (except for MDPREF map). When the consumer co-ordinates were superimposed into a preference map, consumer co-ordinates lost connections to product co-ordinates. Though PLS1 and PLS2 were constructed to solve this lack of connection, the percent variance explained among consumers did not show improvement in the variance explained values. This was especially true in the fragrance study preference maps as they had a decrease in the number of consumers who mapped closest to their most-liked products, and a decrease in the percent variance explained in consumers (Table 2.3).

The question may be raised as to whether the product positions in a map should be plotted based on calculation from the consumer or descriptive data. If the product positions in the map were plotted based on consumer data, it could be more accurate in showing which product individual consumers liked, thus improving the number of consumers who map closest to their most-liked products. It also could increase the percent variance explained for consumers. However, not all descriptors would show their true relationship to that particular product (i.e., decrease in the percent variance explained in descriptors). There may be a need to plot product positions that are calculated from both descriptive attributes and consumer data.

When using external preference maps where the product positions are plotted based on calculation from the descriptive attributes, the map is applicable for quantifying or optimizing the attributes. However, the co-ordinate values calculated from different programs were not similar. Ingredient prediction or optimization of intensities from those programs could be different; prediction is unclear at this time. More research by a statistician who knows the estimation theories, how individual multivariate methods and program calculations are set up, and how each program superimposes both descriptive and consumer plots into one is needed to further clarify the findings from this study.

For hedonic data that are complicated (i.e., the fragrance study) preference mapping techniques with a segmentation method may improve interpretation. For researchers to avoid being misled they should interpret a map with the original data background, and create a map of only co-ordinates correlated with particular component axes.

CONCLUSIONS

For uncomplicated data (i.e., the paint study), any method from any program could be implemented because the consumer data are highly homogenous in their preferences. For a less homogenous product's acceptance data (i.e., the milk study), XLSTAT PLS2 or Unscrambler PLS2 (passified) may be the best method because: 1) the percentage variance explained among both descriptors and consumers were almost as high as that of PCA; 2) consumer configuration (overall) is alike; and 3) the number of consumers who map closest to their most-liked products were almost equal to or higher than MDPREF's number.

For heterogeneousness in product preferences and complicated data (i.e., the fragrance study), the MDPREF appeared to be the best method because it gave the highest numbers of consumers who map closest to their most-liked products.

In addition, 2-dimensional visual mapping may be overused, because often the underlying original data is not shown and may not be examined in relation to the maps. In complex studies, products and consumers may appear near each other on the map, but actually have little of the relationship implied.

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Chapter 3

CHAPTER 3 - Computer Clustering May Not be the Best Method for Grouping Consumers to Understand Their Most Liked Products

Abstract

Ensuring that new products satisfy specific groups of consumers can impact successful product development. In sensory studies, cluster analysis has been used to segment consumers. Researchers often analyze mean values of products for consumer segments presuming that the segmented consumers like or dislike similar products. This study investigates how well most/least liked products match for individual members of clusters using various cluster methods in two sensory studies. Four statistical package clustering (SPC) methods were used with hedonic data and data transformed to ranks. Next, the products most frequently rated/ranked highest in each cluster were examined. Four manual clustering groups were extracted and compared to results of the SPC methods. Standard SPC was not found to separate consumers appropriately to understand their ranking/rating of most/least-liked products. For this data, additional manual clustering was necessary to produce consumer cluster segments where consumers within each group had the same highest/lowest scoring products.

Practical Applications

Statistical package clustering (SPC) is a common method for determining consumer clusters, but it may not be the best method for separating consumers or for understanding their most or least liked products. Findings from this research show that the assumption that cluster analysis will produce clusters containing consumers who have the same most or least liked products is false. That is important because it shows that clustering consumers using typical SPC may not produce the homogeneous segments that researchers would like to obtain. This can impact further analyses of data for product optimization and preference mapping. SPC with further manual clustering is recommended for more homogeneous segments. In addition, new SPC methods should be developed that generate cluster segments that are more homogeneous.

Introduction

A product optimized based on product liking scores that is averaged from all consumers in a study may not succeed in the market because it aggregates liking of each consumer whether they rated particular products high or low for liking, or other attributes. Offering consumers "ideal" products based on aggregated data many not provide any consumer with an actual product optimized to specific individual needs. Thus, product developers and marketers often want to create products for groups of consumers who have similar product preferences. To find clusters of consumers who have similar liking patterns, clustering techniques often have been used (e.g. Liggett *et al.* 2008; Carlucci *et al.* 2009; Ares *et al.* 2010; Neely *et al.* 2010; Sinesio *et al.* 2010; Schmidt *et al.* 2010) on overall liking or acceptance data before implementing preference mapping and other statistical techniques. Unfortunately, some studies indicate that cluster analyses were conducted, but failed to specify the mathematical method used (Braghieri *et al.*, 2010; Donadini and Fumi 2010; Lee *et al.*, 2010).

Clustering algorithms used to classify consumer liking patterns are hierarchical, partitional, or density-based (nonparametric) methods (Jain and Dubes 1988; SAS 2005).

Hierarchical clustering is a method measuring similarity or dissimilarity based on distance measurements between two individuals and/or two clusters (nested clusters), e.g., Euclidean distance (Johnson 1998). The algorithm requires a matrix where the distances between all pairs of consumers are given. The hierarchical cluster analysis then sorts all calculated distances and classifies each consumer into a subgroup according to the consumer/subgroup's distances from one another. In this case, the sum of squared distances reflects the total differences in liking scores described by participants as his/her liking. To further merge the subgroups into a hierarchy of clusters, various linkage methods are available, e.g., Ward's (Childs *et al.* 2009; Sabbe *et al.* 2009; Mahanna and Lee 2010; Felberg *et al.* 2010; Sinesio *et al.* 2010), average (Gámbaro *et al.* 2007), and complete linkage (Liggett *et al.* 2008). More information about these methods is available in Johnson (1998), Meullenet *et al.* (2007), Banfield and Raftery (1993), and Meilă and Heckerman (1998).

Although hierarchical clustering is designed to merge subgroups together until they are all in one large group, partitional algorithms do the opposite. A familiar algorithm that accomplishes this separation is known as k-means clustering, where consumers are partitioned from one large group into many smaller clusters (MacQueen 1967; Resano *et al.* 2009).

Last, the density-based algorithm defines a cluster for an area that has a higher density of consumers than the cluster's surrounding area (Dash *et al.* 2001). Unlike the other algorithms, density-based clustering does not have to specify the number of clusters, instead it uses either the number of "neighbors" or maximum radius of the sphere to calculate clusters. This algorithm is not a popular tool in sensory science, as of yet, and was found in only one study (MacKay and O'Mahony 2002).

In many consumer studies, clustering consumer products based on liking/acceptability often yields non-distinct clusters where the cluster members overlap when they are plotted in a biplot (Young *et al*. 2004; Carbonell *et al.* 2008; Wajrock *et al.* 2008). For easier understanding and future use (e.g., ingredient optimization) the results of a clustering analysis often are presented as group means for each of the clusters (Childs and Drake 2009; Sinesio *et al.* 2010).

When using clustering, researchers often expect a cluster to represent a group of consumers who, at least, rate the same products as among either their most or least-liked products. For example, a cluster that contained consumers who disagreed on what products were well liked and which were least liked would not be seen by most scientists or marketers as a true consumer cluster. However, cluster algorithms do not use just the highest and lowest scored products; instead they use the total data set to create the cluster. Thus, it is not clear how well using the overall pattern of liking for all products impact the grouping of consumers into segments with the same high and low liked products. There is limited research to demonstrate how well the preference pattern of a cluster complements individual member liking patterns. The grouping of consumers with similar high and low liked products would seem to be particularly important when data from consumer segments is further analyzed to predict liking for future products. Products at the high and low end have a major impact on the regression algorithms used to define future products or key attributes in the category. The objectives of this study were to determine 1) whether various SPC methods differ in their ability to group individuals whose most-liked (or least liked) products were the same as other consumers in that cluster, and 2) to develop alternative procedures that could improve the homogeneity of the cluster analysis results if needed.

Materials and Methods

Data Source

Two consumer studies, a milk study (Adhikari *et al.* 2010) and a fragrance study (Retiveau 2004), were examined. These studies varied in the number of samples, number of consumers, types of products, and variability in the data (Chapter 2). The milk study had less complicated data than the fragrance study. In the milk study six products were tested and consumers generally gave one product (REG3) the highest and one product (LFA0) the lowest overall liking scores. There were small differences in liking for some consumers (Adhikari *et al*. 2010) and it was reasonable to segment the data. The fragrance study included 22 samples and was not homogenous in product liking or disliking. For example, consumers gave multiple products (621, 517, 237, 638, and 211) the highest scores but only one product (412) the lowest scores for liking (Retiveau 2004).

Clustering Methods

This study implemented two main types of segment classification, statistical package clustering methods or SPC (numerical clustering methods offered by various statistical packages, e.g., hierarchical, partitional and density-based methods), and manual clustering methods (based on the first or second most frequently liked/disliked products). SPC procedures used included various hierarchical cluster analyses (McQuitty's similarity analysis or MCQ, median, single linkage, complete linkage, Ward's and average linkage methods), a partitional algorithm (k-means), and a nonparametric method (method = 1 by PROC MODECLUS; method = twostage by PROC CLUSTER, two-stage density linkage). All methods were carried out using SAS version 9.2 (SAS Institute, Cary, NC, USA), using both hedonic ratings and, separately, ranking scores that were transformed from hedonic ratings. For both the milk and fragrance studies, the number of clusters using SPC was determined by using the Cubic Clustering Criterion, pseudo-F and pseudo-t statistics, and by visually examining dendrograms calculated using Ward's clustering method. Figures 3.1 and 3.2 illustrate three clusters for the milk study and 11 clusters for the fragrance study. The largest (size) cluster was named Cluster 1, Cluster 2 had the next largest number of members, and so forth. These clusters were named as SPC clusters for this research.

Manual clustering also was done beginning with the initial SPC clusters from each method. Manual clustering based on a) most frequently liked products, or b) most frequently liked and most frequently disliked products was done to refine the clusters. The procedures for selecting consumers for each manual cluster method started with each SPC cluster using techniques described in Table 3.1.

For each SPC method, analysis of variance tests (ANOVAs) were run using PROC GLIMMIX where sample, consumer and sample×cluster were treated as fixed effects; and consumer within a cluster was treated as a random effect. Mean separation (Tukey-Kramer tests, $\alpha = 0.05$) was conducted on the liking data in each cluster to determine if the acceptance patterns across clustering method were similar.

For individual manual clusters, ANOVA tests were run using PROC GLIMMIX (sample was treated as a fixed effect; consumer was treated as a random effect), and mean separation using Tukey-Kramer tests, $\alpha = 0.05$.

TABLE 3.1 LIST OF MANUAL CLUSTERING METHODS

Manual Clustering Name	Definition	Example
Strict	Cluster limited to consumers who gave the most frequently liked product and the most frequently disliked product their highest and lowest scores, respectively.	In SPC Cluster 1 more people scored product A highest and product Z lowest. Thus, this cluster is limited to those people who gave product A their highest score and product Z their lowest score.
Strict - Liking Only	Cluster limited to consumers who gave the most frequently liked product their highest score	In SPC Cluster 1 more people scored product A highest. Thus, this cluster is limited to those people who gave product A their highest score.
Loose	Cluster limited to consumers who gave the most frequently liked product and the most frequently disliked product either their highest or next to highest score and lowest or next to lowest scores, respectively.	In SPC Cluster 1 more people scored product A highest and product Z lowest. Thus, this cluster is limited to those people who gave product A either their highest or next to highest score and product Z their lowest or next to lowest score.
Loose – Liking Only	Cluster limited to consumers who gave the most frequently liked product their highest or next to highest score	In SPC Cluster 1 more people scored product A highest. Thus, this cluster is limited to those people who gave product A either their highest or next to highest score.

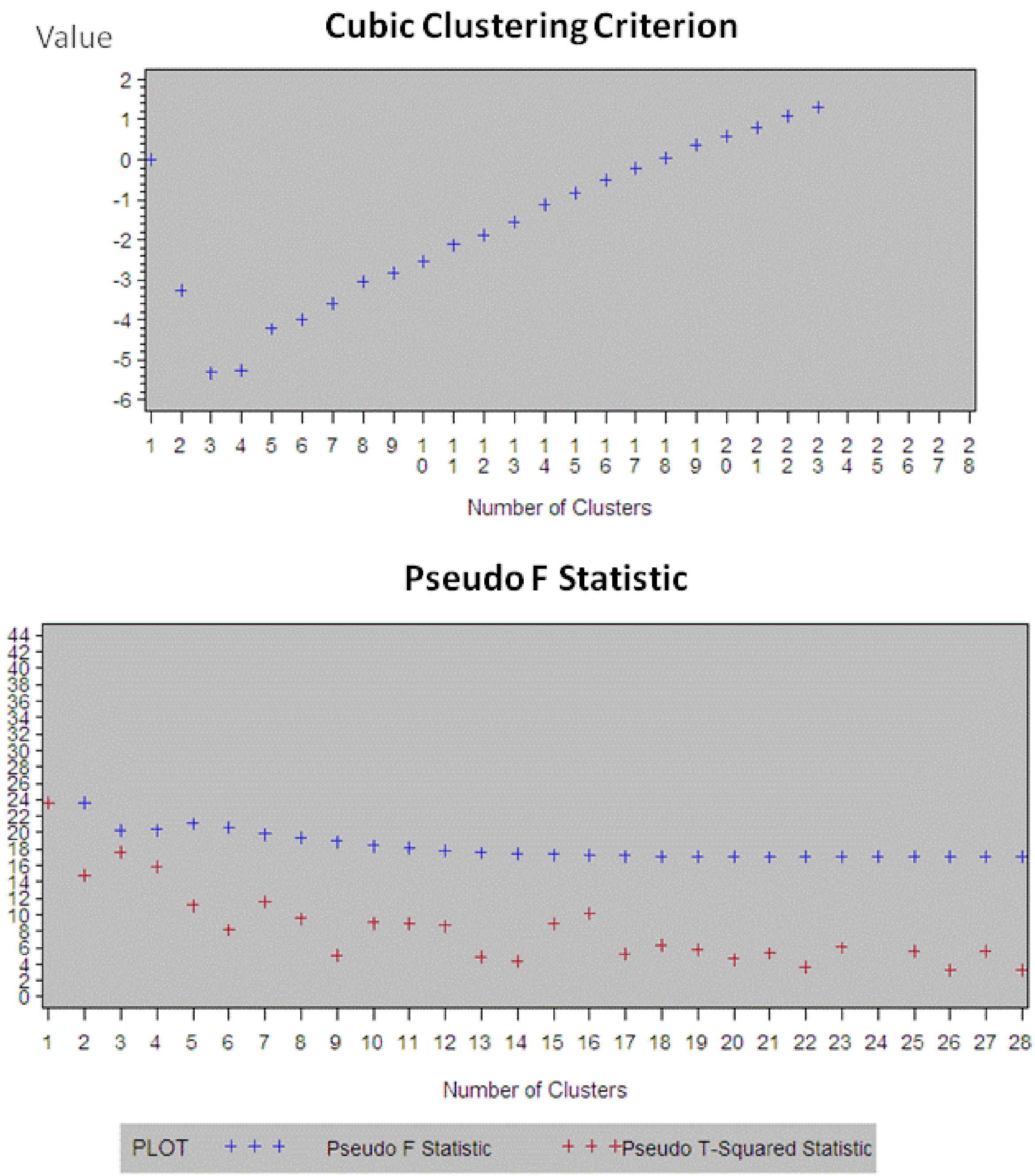

FIG. 3.1 CRITERIA PLOTS FOR DETERMINING THE NUMBERS OF CLUSTERS IN THE MILK CONSUMER DATA

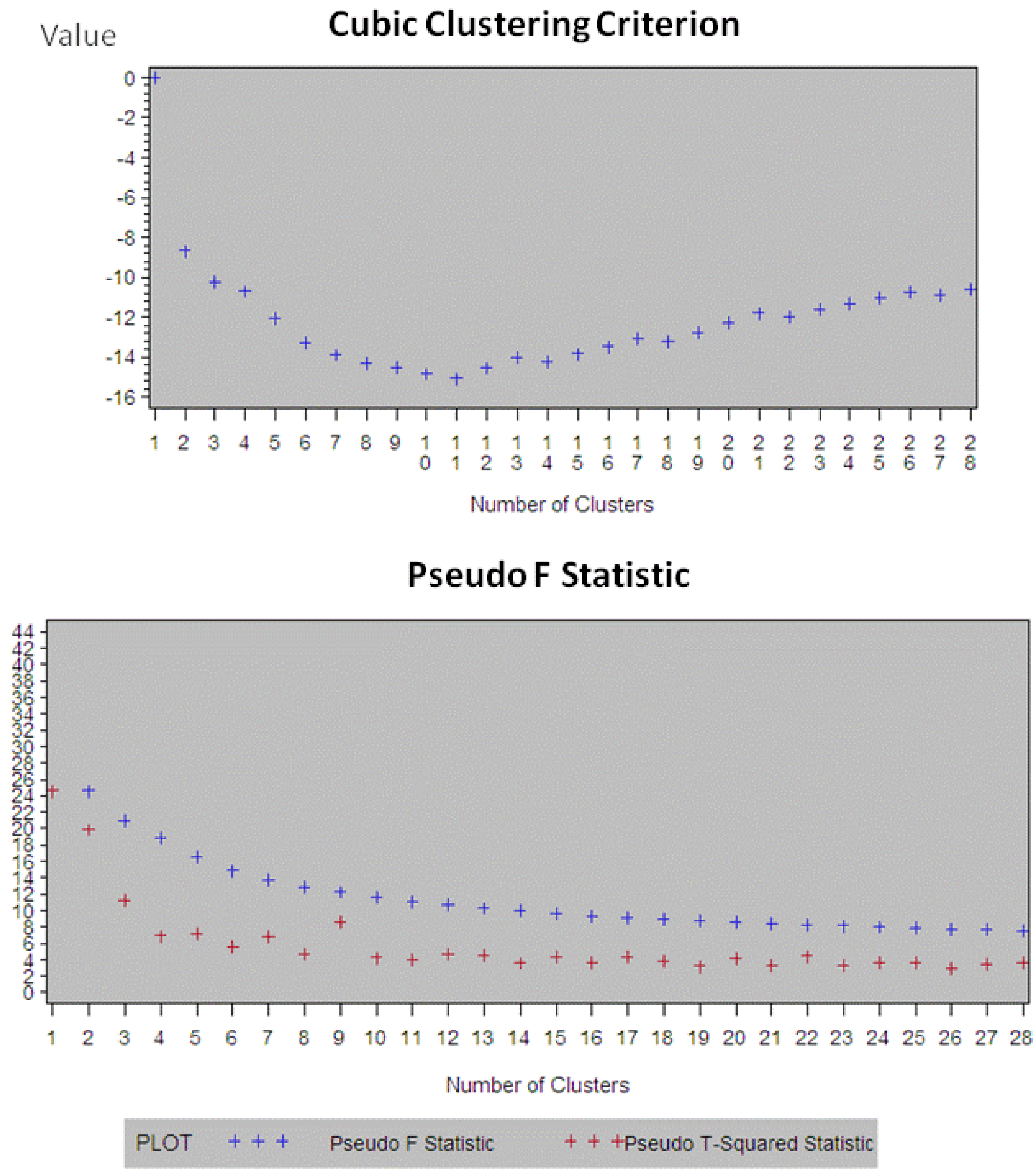

FIG. 3.2 CRITERIA PLOTS FOR DETERMINING THE NUMBERS OF CLUSTERS IN THE FRAGRANCE CONSUMER DATA

Comparisons of SPC methods based on hedonic versus rank scores, and SPC methods versus manual clustering methods were made based on:

1. Consumers in clusters
   - size of clusters
   - members within the cluster
   - number of consumers common to both SPC and manual clustering
2. Most frequently liked/disliked products of SPC based on hedonic versus rank scores
3. Mean comparisons of consumer subgroups determined by ANOVA and comparison of the order of products with the highest, median, and lowest liking means
4. Comparison of ranges of product means between the SPC and manual clusters.

Results and Discussion

Nonparametric, median, single and average cluster analyses often clustered consumers into one large group (Supplementary results for chapter 3). When only one large cluster is found that increases the probability of having all consumers who prefer a product become part of that cluster, e.g., product REG3 in the milk study or product 517 in fragrance study. It also increases the probability that people who did not choose that product as their most liked to become part of that cluster as well. For example, in the MCQ clustering method if one cluster contained 102 members out of 115 total consumers in the milk study then this cluster likely would contain all 59 consumers who prefer product REG3, but also would include 43 consumers who chose a different product as their most liked product. Therefore, to have comparisons across groups and clustering methods, only methods that yielded a number of members of the largest group within ±30% of the frequency of the most liked product in either the milk or fragrance study were retained. In the milk study product REG3 was scored highest by 59 consumers and in the fragrance study product 517 was scored highest by 110 consumers. Thus, cluster methods that resulted in the largest cluster having between 41-77 consumers (milk study) or 77-143 consumers (fragrance study) were maintained and examined further. This resulted in only complete linkage, k-means, Ward's and MCQ clustering methods being retained for this study.

Results of SPC analyses (complete linkage, k-means, Ward's and MCQ methods) and manual cluster analyses (strict, strict-liking only, loose, loose-liking only clusters) based on both hedonic ratings and on transformed rank scores indicated that three clusters for milk and 11 clusters for fragrance were the most appropriate across the methods. Comparisons were made on the three largest clusters in each study.

Consumers in clusters – SPC comparisons

The use of score types (hedonic or rank) and clustering methods had a tremendous impact on the cluster members; not a single consumer was common[1] to Cluster 1 for all scores types and methods. (Note: The members of Cluster 1, the largest cluster, for the SPC methods used for the milk and fragrance studies are available in Table 3.2). For the cluster analyses based on rating scores in the milk study, Cluster 1 contained 22 common consumers across all methods and contained fewer than 10 common consumers when clustering was based on rank (Table 3.3A). The same results also were found in the fragrance study (Table 3.3B); when clustering used rating scores, it produced more common consumers than when using ranking scores.

In the milk study, based on the raw scores, Cluster 1, 2 and 3 had 55, 41, and 19 members for complete linkage; 41, 39, and 35 members for k-means; and 102, 11, and 2 members for Ward's method, respectively. (Note: Table 3.3A,B show the number of members in each cluster.) Each cluster is named according to its size from large to small (Cluster 1, 2, and so forth). No method produced the same cluster size in cluster 1, 2 or 3, regardless of whether clustering individuals using their rating or rank scores.

[1] Common consumers are consumers assigned to the same cluster across methods.

TABLE 3.2 CONSUMER MEMBERS IN EACH COMPUTER GENERATED CLUSTER

(A) MILK STUDY'S CLUSTERS

Types of score	Method	Consumers
Cluster 1		
Rating	Complete linkage	3 4 7 8 10 11 12 15 17 20 25 28 29 31 35 36 38 39 42 44 45 47 48 49 50 51 55 56 57 60 63 65 70 72 76 77 78 79 83 84 88 89 92 94 96 97 99 102 104 106 107 110 111 112 115
	K-means	3 4 7 8 9 12 13 14 15 17 23 30 31 40 42 45 49 50 51 52 55 57 63 65 71 75 76 77 82 84 92 94 96 97 99 101 103 110 111 114 115
	Ward's	3 4 5 7 9 12 14 15 23 30 31 40 45 49 50 51 52 56 57 60 62 63 64 65 66 71 75 77 78 82 84 88 92 94 96 97 99 101 103 104 110 111 112 114
	MCQ	1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 57 58 60 62 63 64 65 70 71 72 74 75 76 77 78 79 81 82 83 84 85 86 87 89 90 91 92 93 94 95 96 97 98 99 101 102 103 104 105 106 107 109 110 111 112 113 115
Ranking	Complete linkage	3 4 7 9 12 15 20 28 30 31 43 44 45 48 49 50 51 55 57 60 63 65 72 75 77 78 82 84 88 92 94 96 97 99 101 104 110 111 112 114
	K-means	1 2 5 6 10 18 21 22 24 25 26 27 29 32 33 36 37 38 46 53 54 56 58 59 61 62 66 67 68 69 70 73 74 79 80 81 83 85 86 87 89 90 91 93 95 98 100 102 105 108 109 113
	Ward's	1 5 18 21 24 27 29 32 36 37 38 46 53 56 58 59 61 62 66 67 68 69 73 74 80 81 85 86 87 89 90 91 93 98 100 102 105 108 109 113
	MCQ	1 2 4 5 6 10 11 12 13 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 41 43 44 46 48 53 54 56 57 58 59 60 61 62 66 67 68 69 70 72 73 74 75 76 79 80 81 82 83 85 86 87 89 90 91 93 94 95 97 98 99 100 101 102 103 104 105 106 108 109 111 113

Types of score	Method	Consumers
Cluster 2		
Rating	Complete linkage	1 2 6 18 19 21 22 24 26 27 32 33 37 40 43 46 53 54 58 59 61 64 67 68 69 73 80 81 85 86 87 90 91 93 95 98 100 105 108 109 113
	K-means	1 2 5 6 16 19 21 22 24 26 27 33 34 37 41 53 54 58 59 61 62 64 66 68 69 74 78 81 86 87 90 93 98 100 104 105 108 109 113
	Ward's	1 2 6 13 16 18 19 21 22 24 26 27 32 33 34 35 37 41 43 46 53 58 59 61 67 68 69 73 74 80 81 85 86 87 90 91 93 98 100 105 108 109 113
	MCQ	56 59 61 67 68 69 73 80 88 100 108
Ranking	Complete linkage	1 10 21 24 26 27 32 33 37 38 53 56 58 59 61 62 67 68 69 70 73 74 80 81 85 86 87 90 91 93 95 98 100 102 103 105 108 109 113
	K-means	3 4 7 11 12 15 17 20 23 28 30 31 39 43 44 48 57 60 63 65 72 75 76 77 82 88 92 94 97 99 101 103 104 106 110 111 112 114
	Ward's	2 4 6 10 11 12 15 20 22 23 26 28 30 31 33 39 43 44 48 54 57 60 70 72 75 79 82 83 88 94 95 97 99 101 103 104 106 111 112
	MCQ	3 7 40 45 49 50 51 55 63 64 65 77 78 84 88 92 96 110 112 114
Cluster 3		
Rating	Complete linkage	5 9 13 14 16 23 30 34 41 52 62 66 71 74 75 82 101 103 114
	K-means	10 11 18 20 25 28 29 32 35 36 38 39 43 44 46 47 48 56 60 67 70 72 73 79 80 83 85 88 89 91 95 102 106 107 112
	Ward's	8 10 11 17 20 25 28 29 36 38 39 42 44 47 48 54 55 70 72 76 79 83 89 95 102 106 107 115
	MCQ	66 114
Ranking	Complete linkage	2 5 6 8 11 13 14 16 17 18 19 22 23 25 29 34 35 36 39 40 41 42 46 47 52 54 64 66 71 76 79 83 89 106 107 115
	K-means	8 9 13 14 16 19 34 35 40 41 42 45 47 49 50 51 52 55 64 71 78 84 96 107 115
	Ward's	3 7 8 9 13 14 16 17 19 25 34 35 40 41 42 45 47 49 50 51 52 55 63 64 65 71 76 77 78 84 92 96 107 110 114 115
	MCQ	8 9 14 42 47 52 71 107 115

(B) FRAGRANCE STUDY'S CLUSTERS

Types of score	Method	Consumers
Cluster 1		
Rating	Complete	1 5 10 11 12 13 16 27 28 30 34 46 50 51 53 57 58 61 62 64 66 75 76 78 79 89 91 94 96 98 100 104 107
	linkage	108 111 112 114 119 120 121 130 132 138 140 146 157 159 166 173 205 218 227 235 239 242 255 257 258 262 270 271 301 303 315 316 317
		329 331 332 333 335 336 347 352 355 356 358 360 362 368 373 383
	K-means	3 6 7 8 9 11 12 16 17 21 25 26 30 33 35 36 39 40 42 43 45 49 50 55 58 65 67 73 74 76 77 81 83
		86 95 97 99 101 103 104 106 110 114 115 117 119 122 127 130 131 137 138 143 144 147 148 149 152 153 156 158 161 164 169 170 173
		203 210 211 214 215 217 221 222 233 234 236 239 240 241 245 246 253 256 257 260 262 263 270 272 273 275 277 278 280 282 283 306 313
		317 318 319 320 321 322 325 342 344 352 357 360 362 363 364 367 369
		375 381 383 384
	Ward's	1 10 12 13 25 28 46 51 55 62 63 67 72 74 76 78 91 95 96 98 99 112 130 132 138 140 172 218 221 227 233 234 239
		242 246 254 257 258 262 270 271 315 332 333 335 336 344 349 355 358 369 372 382 384
	MCQ[1]	1 4 5 11 12 13 17 19 21 22 23 25 27 30 32 33 34 35 37 38 39 42 43 44 45 46 48 50 51 52 53 57 61
		63 64 66 67 71 72 73 74 75 76 77 78 79 81 82 83 84 87 90 91 94 96 97 98 99 100 101 104 106 107 114 115 116
		118 119 120 121 122 124 125 127 130 131 132 134 135 138 139 140 145 146 150 151 154 156 157 160 166 171 172 205 213 215 218 220 225
		227 237 244 248 268 271 273 279 301 303 304 310 312 313 314 315 317 318 326 331 333 334 335 336 341 342 344 348 349 352 355 358 359
		360 361 362 365 368 369 376 381 383 384
Ranking	Complete	2 7 8 36 40 41 53 58 66 69 75 77 84 85 88 92 101 115 124 139 141 143 154 167 170 202 206 207 208 212 214 219 223
	linkage	226 228 232 234 240 243 253 259 263 265 266 267 272 273 276 278 281 282 283 301 302 307 308 323 327 330 331 338 349 351 364 368 371
		374 375 376 378 382 384
	K-means	4 20 33 36 37 41 45 46 49 53 60 65 69 70 71 74 77 84 86 92 100 101 102 106 108 109 117 124 125 127 130 131 132
		137 141 143 148 149 158 165 171 202 204 205 212 214 223 225 226 230 231 235 237 239 240 243 246 260 261 262 265 266 267 270 271 273
		280 282 283 308 320 321 326 329 336 337 344 347 349 353 357 364 375 382
	Ward's	2 7 23 29 47 77 85 88 89 90 92 105 109 114 120 139 141 142 143 145 154 164 202 206 209 211 212 214 222 223 231 232 243
		249 252 256 259 261 266 267 272 273 281 282 283 301 302 303 307 308 310 312 314 323 325 329 331 338 339 348 351 353 359 371 374 378
	MCQ	7 8 11 12 23 25 27 29 37 40 41 47 53 61 63 66 67 69 72 73 74 75 76 84 85 89 90 98 99 101 104 107 109
		114 115 118 120 121 122 124 125 130 134 135 138 142 143 145 147 149 163 165 167 170 201 207 208 209 211 212 219 222 226 227 228 231
		234 235 237 240 243 249 251 252 253 256 261 263 264 270 272 273 276 278 282 303 305 307 308 310 312 314 315 323 325 327 329 330 333
		335 336 338 340 341 342 344 348 353 359 363 365 368 369 371 375 376 378 382 384

Types of score	Method	Consumers
Cluster2		
Rating	Complete	3 4 6 7 8 9 25 26 36 39 40 43 49 55 63 65 70 72 95 97 99 102 103 110 115 117 137 143 144 147 149 152 153
	linkage	158 161 164 168 169 170 203 384 210 211 214 221 222 233 234 236 240 241 245 246 253 256 260 263 269 275 277 278 280 282 283 306 319
		320 321 322 325 344 357 363 364 367 369 375 381 382
	K-means	2 5 19 27 29 34 37 41 44 47 52 53 66 69 70 71 75 84 85 87 89 90 91 92 102 105 109 116 120 121 124 139 141
		142 145 154 159 163 165 167 171 201 202 205 206 207 208 209 212 219 223 225 226 228 231 235 243 244 249 251 252 258 259 261 264 266
		267 268 276 281 284 301 302 304 305 307 308 310 314 323 324 327 329 331 338 339 340 341 351 353 359 365 368 371 374 378 382
	Ward's	2 4 19 29 77 85 92 97 106 139 141 142 201 206 207 208 212 219 223 228 243 249 252 261 264 266 267 272 276 281 302 305 307
		314 323 338 339 351 353 359 371 378 381
	MCQ[1]	2 3 6 7 8 9 10 16 28 29 36 40 41 49 55 62 65 70 85 86 89 92 95 102 103 105 108 109 110 112 117 137 141
		142 143 144 147 148 149 152 153 158 159 161 163 164 169 170 173 201 203 206 207 208 210 211 212 214 217 219 221 222 223 228 231 233
		234 235 236 239 240 241 242 243 245 246 249 251 252 253 256 257 258 260 261 262 263 264 266 267 270 272 275 276 277 278 280 281 282
		283 305 306 307 319 320 321 322 323 325 327 329 332 338 339 340 347 351 353 356 357 363 364 367 371 374 375 378 382
Ranking	Complete	1 13 43 46 49 52 57 70 83 87 89 91 96 102 109 111 117 132 137 145 153 201 204 227 230 231 237 244 249 258 261 262 270
	linkage	271 275 280 284 306 310 312 322 329 333 335 344 353 355
	K-means	1 3 6 9 10 12 13 23 24 25 28 48 51 52 55 59 62 63 72 76 94 96 97 98 99 103 104 112 116 119 123 135 138
		147 150 153 160 169 210 218 221 222 227 233 242 254 255 257 274 275 315 318 319 332 333 335 346 358 372 381
	Ward's	6 36 37 50 53 59 62 75 103 106 125 130 140 158 172 204 226 227 237 239 240 250 270 279 284 315 318 326 333 335 336 344 349
		364 367 375 382
	MCQ	1 2 9 13 17 20 26 33 34 36 43 46 49 51 52 55 57 60 64 70 71 77 86 87 88 91 92 95 96 100 102 105 108
		111 116 117 129 131 132 137 139 141 148 153 154 158 160 164 168 202 203 204 205 206 214 218 220 223 230 232 236 238 241 244 254 258
		259 262 265 266 267 269 271 275 280 281 283 284 301 302 306 322 324 326 331 339 346 349 351 357 358 364 372 374

Types of score	Method	Consumers
Cluster3		
Rating	Complete linkage	19 23 37 71 74 77 84 85 92 106 109 118 124 125 127 131 135 155 163 165 171 172 207 215 223 225 231 237 243 249 251 261 266 268 272 276 302 308 310 313 323 327 330 337 340 349 353 359 371 374 376
	K-means	1 4 10 13 14 22 23 24 28 32 38 46 48 51 57 59 61 62 63 68 72 78 79 82 93 94 96 98 107 108 111 112 118 123 125 126 128 132 133 135 140 146 150 151 155 157 160 166 168 172 213 218 220 227 230 237 238 242 248 255 265 269 271 274 279 303 312 315 326 330 332 333 334 335 336 337 345 346 347 348 349 355 356 358 361 373 376
	Ward's	27 35 41 43 50 52 53 66 75 81 84 87 101 104 114 115 116 119 121 122 124 160 163 167 209 244 251 268 274 304 327 340 341 368
	MCQ[1]	66 144
Ranking	Complete linkage	20 23 28 29 30 33 37 55 60 62 64 72 93 95 99 100 104 106 114 116 129 140 142 157 158 160 172 211 221 239 252 254 314 325 326 339 346 348 354 359 367 373
	K-means	2 7 8 29 47 50 82 85 87 89 90 114 120 122 139 142 145 201 206 208 209 211 232 249 252 253 256 263 272 276 281 284 301 302 305 307 310 314 323 325 338 339 340 348 351 359 368 371 374 378
	Ward's	14 30 33 35 41 60 66 67 69 70 71 73 81 86 100 101 108 129 131 144 148 149 156 157 245 263 264 320 321 342 357 360 363 365
	MCQ	5 14 16 19 39 42 65 68 78 83 93 94 110 119 123 127 128 133 150 152 159 166 169 173 215 225 313 321 352 354 356 362 383

[1] MCQ method yields only 2 large groups(Cluster 1 and 2) containing ±30% of the frequency of the most liked product in a study; Cluster 3 is considerably small in size

Results of having few common consumers in each cluster and different numbers of members in a cluster are dependent on the method used. Specific algorithms used to determine clusters could have an impact on the clustering, e.g., complete linkage and Ward's can produce different clusters because of the way they calculate the group members. To merge two members into one cluster, for example, complete linkage uses the maximum distance between all pairs of members (SAS Institute Inc. 2009) while average linkage uses group's average distances and single linkage uses the distance to the nearest neighbor. Ward's method assigns a consumer to a cluster that minimizes the squared Euclidean distance to the cluster mean. K-means clustering partitions people based on their ratings into a specified cluster number, and then assigns each consumer to the subgroup whose centroid (mean of all products within the cluster) is closest (Johnson and Wichern 1988) to the individual consumer (not calculating the distance measurements between individuals as the Ward's method and complete linkage methods do). Problems with these clustering methods illustrate that a cluster structure (a cluster tree) from the single linkage method was often unbalanced with too many layers and chaining clusters. The complete or average linkage methods were unsuccessful in cluster separation (Jain and Dubes 1988; Everitt *et al.* 2001) because the range of the distances that the methods calculated for cluster fusion was small. Therefore, the dendograms from the complete and average methods were difficult for researchers to specify believable clusters. The k-means method tended to cluster all consumers into one large cluster. Clustering using Ward's method yielded the same size clusters (Everitt *et al.* 2001), which may not accurately portray true clusters. However, its cluster tree makes it easier to identify clusters than other methods.

Consumers in clusters – SPC to Manual Clustering comparisons

The comparisons of common consumers between SPC clusters and manual clusters (for the milk study) indicate clusters based on ranking data yield slightly more common consumers than clusters based on rating data. The opposite result was found in the fragrance study when clustering based on rating data gave more common consumers than clusters based on ranking data.

TABLE 3.3 NUMBER OF CONSUMERS, MOST FREQUENTLY HIGH-RATED LIKED/DISLIKED PRODUCTS, NUMBER AND PERCENTAGE OF CONSUMERS WHO WERE ALSO GROUPED IN THE STRICT, STRICT-LIKING-ONLY, LOOSE OR LOOSE-LIKING-ONLY CLUSTER FOR EACH STATISTICAL PACKAGE GENERATED CLUSTER

(A) OF THE MILK STUDY

Types of score	Method	Cluster	Number of members	Liked products	Disliked products	Intersection with							
						Strict	%	Strict liking only	%	Loose	%	Loose liking only	%
Rating	Complete linkage	Cluster 1	55	REG3	LFA0	13	17	27	31	29	32	42	42
		Cluster 2	41	REG3	LFA0	19	35	24	32	31	42	35	38
		Cluster 3	19	REG2	REG0	5	23	9	20	8	24	9	14
	K-means	Cluster 1	41	LFA3	REG0/REG2	17	39	18	34	27	56	27	45
		Cluster 2	39	REG3	LFA0	14	24	25	34	26	34	34	37
		Cluster 3	35	REG3	LFA0	16	31	18	24	28	39	31	34
	Ward's	Cluster 1	44	REG3	REG2	14	29	22	27	22	40	28	27
		Cluster 2	43	REG3	LFA0	17	29	27	36	30	39	38	41
		Cluster 3	28	LFA3	LFA0	9	26	11	23	12	26	14	23
	MCQ	Cluster 1	102	REG3	LFA0	25	23	49	44	55	50	77	69
		Cluster 2*	11	REG3	LFA0	8	–	10	–	9	–	10	–
		Cluster 3*	2	LFA3/REG0/REG2	REG3	0	–	0	–	0	–	0	–
Ranking	Complete linkage	Cluster 1	40	LFA2/REG3	REG2	18	39	28	33	25	49	33	32
		Cluster 2	39	REG3	LFA0/REG0	21	36	26	36	32	40	35	39
		Cluster 3	36	REG2	LFA0	11	23	21	43	16	28	31	52
	K-means	Cluster 1	52	REG3	LFA0	24	39	29	35	41	55	44	46
		Cluster 2	38	LFA3	LFA0	12	29	27	66	24	55	36	75
		Cluster 3	25	REG3	LFA2	9	29	13	18	10	24	15	15
	Ward's	Cluster 1	40	REG3	LFA0	17	30	22	29	29	39	32	34
		Cluster 2	39	LFA3/REG3	LFA0	21	36	30	35	34	46	39	39
		Cluster 3	36	REG3	REG2	8	17	18	23	10	17	20	19
	MCQ	Cluster 1	86	REG3	LFA0	32	37	46	46	61	69	72	71
		Cluster 2*	20	REG3	REG2	1	–	12	–	3	–	12	–
		Cluster 3*	9	LFA0	LFA3/REG0	0	–	1	–	0	–	3	–

Liked products = the most frequently high-rated by consumers for best-liked products
Disliked products = the most frequently low-rated by consumers for least-liked products
* The percentage of consumers who were grouped in to manual clustering groups (strict, strict liking only, loose, loose liking only cluster) is not calculated because it is too small a cluster size

(B) OF THE FRAGRANCE STUDY

Types of score	Method	Cluster	Number of members	Liked products	Disliked products	Intersection with							
						Strict	%	Strict liking only	%	Loose	%	Loose liking only	%
Rating	Complete linkage	Cluster 1	82	621	196	6	6	26	16	21	15	58	24
		Cluster 2	79	517	318	12	13	38	25	27	20	58	26
		Cluster 3	51	237	412	11	16	21	16	35	28	43	20
	K-means	Cluster 1	120	517	492	10	8	51	28	33	20	88	38
		Cluster 2	97	237	196	18	16	36	22	56	39	79	35
		Cluster 3	87	621	412	17	16	17	16	43	26	69	30
	Ward's	Cluster 1	54	621	492	2	3	12	8	7	5	33	14
		Cluster 2	43	759	318	12	21	20	22	24	24	32	19
		Cluster 3	34	237/638	196/219	5	6	17	11	15	9	25	10
	MCQ	Cluster 1	142	517	412	8	5	43	21	43	20	86	34
		Cluster 2	128	517	318	21	16	53	29	50	31	89	37
Ranking	Complete linkage	Cluster 1	72	237	196	19	22	37	27	44	34	63	29
		Cluster 2	47	621	318/910	5	5	24	18	36	23	42	19
		Cluster 3	42	237	318	4	6	16	13	17	15	32	15
	K-means	Cluster 1	84	621	412	17	16	17	16	46	29	73	32
		Cluster 2	60	621	318	13	15	28	20	30	24	52	23
		Cluster 3	50	638	412	10	15	23	21	30	23	41	21
	Ward's	Cluster 1	66	517	412	13	15	28	19	36	25	48	22
		Cluster 2	37	621	318	11	17	19	33	18	13	32	15
		Cluster 3	34	715	492	7	18	18	21	16	23	27	17
	MCQ	Cluster 1	119	237	196	23	18	56	34	56	34	97	43
		Cluster 2	94	621	412	18	16	18	16	45	26	77	33
		Cluster 3	33	621	196	4	7	16	13	11	11	24	11

Liked products = the most frequently high-rated by consumers for best-liked products
Disliked products = the most frequently low-rated by consumers for least-liked products

The number of common consumers who were manually partitioned into strict, strict-liking-only, loose, or loose-liking-only groups is available in Table3.3A,B. Regardless of the manual clustering methods used and types of ratings, none of the SPC based methods consistently yielded clusters with high percentages of common consumers. For less complicated data (i.e., the milk study) the percentages of common consumers for SPC based methods is less than 39% for strict manual clustering (MC), <66% for strict-liking only MC, <69% for loose MC, and <75% for loose-liking only MC, whereas, common consumer percentages for complex data (i.e., the fragrance study) for SPC based methods were less than 22% for strict MC, <34% strict-liking only MC, <39% for loose MC, and <43% for loose-liking only MC. No SPC algorithm did a better job than any other for segmenting individuals that had similar most-liked products versus least-liked products.

Most Frequently Liked and Disliked Products of SPC Based on Hedonic Versus Rank Scores

The frequency of products rated or ranked highest and lowest for members of each cluster are given in Tables 3.4-3.5A,B. The different clustering methods generally did not produce the same highest and lowest liked products for all clusters.

For the milk study there were 24 clusters from all the methods used in this study. Table 3.4A,B illustrates the most frequently liked and disliked products across clusters and SPC methods for both rating and rank scores. When looking at each cluster from various methods the most frequently liked/disliked products of Cluster 1, using k-means or Ward's methods on the rating scores, are LFA3/REG0 & REG2 and REG3/REG2, respectively. These products are different from the results of complete linkage or MCQ methods. The most frequently liked/disliked products of Cluster 2 using all methods are the same; the most frequently liked/disliked products of Cluster 3 using k-means or Ward's methods are different products from the results of complete linkage or MCQ methods. When considering all clusters together 13, out of 24 clusters, resulted in the highest liking score for product REG3 and the lowest liking for LFA0 (the most frequently liked and disliked products, respectively). One out of the 24 clusters gave a cluster that could not specify consumers liking (i.e. too few members and consumers disagreed in their liking opinions, Cluster 3 using MCQ on hedonic scores). The remaining 10 clusters (Table 3.4A,B) showed consumers rating/ranking products in one of the following liking patterns:

a) Product LFA3/REG2&REG3 the most frequently liked/disliked products,
b) Product REG3/REG2 the most frequently liked/disliked products,
c) Product REG2/REG0 the most frequently liked/disliked products,
d) Product LFA3/LFA0 the most frequently liked/disliked products,
e) Product LFA0/and LFA3&REG0 the most frequently liked/disliked products.

Clearly, the results show differences in most frequently liked and disliked products depending on the clustering methods chosen. That would be a major problem for researchers trying to decide which products should be targeted for certain groups.

The reason why half of all clusters represent the same REG3/LFA0 for their most frequently liked/disliked products likely is because 52% of consumers in the entire milk study chose REG3 as their highest-rated product. This percentage is 50% higher than the second-highest-rated product. Moreover, the REG3-mean-liking score of 6.9 from the overall study is significantly higher than the other samples. LFA0 had a mean liking score of 4.3 (Table 3.4A), the lowest overall score in the study.

In the case of more complicated data, i.e. the fragrance study, the different clustering methods produced noticeably dissimilar most frequently liked and disliked products for all clusters (Table 3.5A,B). Even focusing on each cluster, e.g. Cluster 1, shows that the most frequently liked/disliked products are products 621/196, 517/492, 621/492, and 517/318 using complete linkage, k-means, Ward's, or MCQ methods on the rating scores, respectively. There are 23 clusters from the various SPC methods used in this study. Two clusters each rated 621/196, 517/412 or 621/412 their most frequently liked/disliked products; all other clusters had their own different combination of their most frequently liked/disliked products (Table 3.5A,B).

TABLE 3.4 MEAN PRODUCT LIKING OF THE MILK STUDY

(A) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR ALL CONSUMERS AND INDIVIDUAL COMPUTER GENERATED CLUSTERS

Products	All consumers	Cluster 1				Cluster 2				Cluster 3			
		Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ
	n=115	n=55	n=41	n=44	n=102	n=41	n=39	n=43	n=11	n=19	n=35	n=28	n=2
Like	REG3	REG3	LFA3	REG3	REG3	REG3	REG3	REG3	REG3	REG2	REG3	LFA3	LFA3, REG0, REG2
Dislike	LFA0	LFA0	REG0, REG2	REG2	LFA0	LFA0	LFA0	LFA0	LFA0	REG0	LFA0	LFA0	REG3
LFA0	4.3 c	5.5 c	6.0 a	5.2 ab	4.6 c	2.4 d	2.7 c	2.6 d	1.7 c	4.8 ab	4.0 c	5.5 c	3.0 a
LFA2	5.3 b	6.5 ab	5.9 a	5.4 ab	5.3 bc	4.3 c	3.5 c	4.2 c	5.8 b	4.4 ab	6.7 ab	6.9 ab	2.5 a
LFA3	5.3 b	6.8 a	6.4 a	6.2 a	5.5 b	3.3 cd	3.2 c	3.3 cd	3.0 c	4.9 ab	6.2 b	6.8 ab	6.5 a
REG0	5.5 b	5.6 cb	4.5 b	4.8 cb	5.3 bc	6.2 ab	5.6 b	6.0 b	7.5 a	3.7 b	6.7 ab	6.0 cb	5.5 a
REG2	5.5 b	5.2 c	4.5 b	4.0 c	5.9 b	5.8 b	5.9 ab	6.1 b	2.2 c	6.0 a	6.3 b	7.1 a	4.5 a
REG3	6.9 a	7.2 a	6.3 a	6.3 a	6.9 a	7.2 a	7.0 a	7.2 a	7.9 a	5.3 ab	7.4 a	7.2 a	1.5 a

Product liking for each cluster

Liking was scored on a 9-point hedonic scale; from 1=dislike extremely to 9= like extremely
n = cluster size
Like = the most frequently high-rated by consumers for best-liked products
Dislike = the most frequently high-rated by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a cluster
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a cluster

(B) MEAN CONSUMER RANK SCORES (TRANSFORMED HEDONIC SCALE) FOR ALL CONSUMERS AND INDIVIDUAL COMPUTER GENERATED CLUSTERS

Products	All consumers	Cluster 1				Cluster 2				Cluster 3			
		Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ
	n=115	n=40	n=52	n=40	n=86	n=39	n=38	n=39	n=20	n=36	n=25	n=36	n=9
Like	REG3	LFA2, REG3	REG3	REG3	REG3	REG3	LFA3	LFA3, REG3	REG3	REG2	REG3	REG3	LFA0
Dislike	LFA0	REG2	LFA0	LFA0	LFA0	LFA0, REG0	LFA0	LFA0	REG2	LFA0	LFA2	REG2	LFA3, REG0
LFA0	2.6 c	3.0 b	1.5 d	1.6 c	1.9 d	1.6 d	2.5 c	1.7 c	4.3 a	3.1 bc	4.8 a	4.5 a	5.2 a
LFA2	3.4 b	3.7 b	3.3 b	3.4 b	3.5 bc	3.5 c	4.0 b	3.9 b	2.7 b	2.8 c	2.6 c	2.9 c	4.2 ab
LFA3	3.4 b	4.7 a	2.6 c	2.3 c	3.4 c	2.1 d	5.2 a	4.7 a	4.1 a	3.4 bc	2.6 c	3.3 bc	1.9 c
REG0	3.4 b	2.9 b	4.3 a	4.8 a	3.4 c	4.4 b	2.4 c	2.3 c	4.0 a	2.8 c	3.1 c	3.0 c	2.2 c
REG2	3.6 b	2.0 c	4.4 a	4.2 a	4.1 b	4.1 bc	2.6 c	3.6 b	1.4 c	4.9 a	3.5 cb	3.0 c	4.6 a
REG3	4.6 a	4.7 a	4.9 a	4.7 a	4.8 a	5.3 a	4.4 ab	4.9 a	4.6 a	3.9 b	4.4 ab	4.2 ab	2.9 cb

Product liking for each cluster

Ranking was transfromed from 1-9 point hedonic scale to 1-6 (1 = the least like to 6 = the most like)
n = cluster size
Like = the most frequently high-ranked by consumers for best-liked products
Dislike = the most frequently low-ranked by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean ranking score of a cluster
Solid line box = the median ranking score of a cluster
Dotted line box = the lowest mean ranking score of a cluster

(C) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR INDIVIDUAL STRICT CLUSTERS

Products		Product liking for each cluster										
	Like	LFA0	LFA2, REG3	LFA3	LFA3	LFA3, REG3	REG2	REG2	REG3	REG3	REG3	REG3
	Dislike	LFA3, REG0	REG2	LFA0	REG0, REG2	LFA0	LFA0	REG0	LFA0	LFA0, REG0	LFA2	REG2
	n	6	24	15	20	40	22	8	33	40	15	19
LFA0		8.0 a	4.7 c	3.7 d	5.6 bc	2.8 c	2.9 d	5.8 ab	2.6 c	3.1 c	5.1 bc	4.6 c
LFA2		6.7 abc	6.3 ab	6.2 bc	6.2 b	5.7 b	5.1 c	5.3 bc	5.5 b	5.5 b	3.0 d	5.9 bc
LFA3		5.8 bc	5.8 bc	7.6 a	7.7 a	5.3 b	4.9 c	4.8 bc	4.7 b	4.8 b	4.3 cd	5.6 bc
REG0		5.3 c	6.4 ab	5.6 c	4.5 c	5.8 b	6.2 b	3.6 c	5.8 b	5.4 b	5.9 b	6.8 ab
REG2		7.2 ab	3.2 d	5.9 bc	4.6 c	5.6 b	7.6 a	7.6 a	5.4 b	5.6 b	5.7 bc	2.9 d
REG3		6.5 abc	7.4 a	7.1 ac	6.5 ab	7.7 a	6.6 ab	6.1 ab	7.9 a	7.8 a	7.7 a	7.8 a

Liking was scored on a 9-point hedonic scale; from 1 = dislike extremely to 9 = like extremely
n = cluster size
Like = the most frequently high-rated by consumers for best-liked products
Dislike= the most frequently high-rated by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a cluster
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a cluster

(D) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR INDIVIDUAL LOOSE CLUSTERS

Products		Product liking for each cluster										
	Like	LFA0	LFA2, REG3	LFA3	LFA3	LFA3, REG3	REG2	REG2	REG3	REG3	REG3	REG3
	Dislike	LFA3, REG0	REG2	LFA0	REG0, REG2	LFA0	LFA0	REG0	LFA0	LFA0, REG0	LFA2	REG2
	n	16	36	30	34	69	37	23	64	72	27	33
LFA0		7.3 a	4.6 c	3.9 d	5.7 cd	3.1 c	3.1 d	5.9 b	3.1 c	3.5 c	4.8 bc	4.5 c
LFA2		5.6 b	6.3 ab	6.1 bc	6.4 bc	5.5 b	5.0 c	6.0 b	5.5 b	5.5 b	3.9 c	6.1 b
LFA3		5.0 b	5.8 b	7.2 a	7.5 a	5.3 b	5.3 c	5.7 b	5.1 b	5.2 b	4.8 bc	5.7 b
REG0		5.3 b	5.9 b	5.3 c	5.0 de	5.7 b	5.9 bc	4.4 c	5.7 b	5.5 b	5.9 b	6.1 b
REG2		6.3 ab	3.6 c	5.6 c	4.5 e	5.7 b	7.4 a	7.4 a	5.7 b	5.8 b	5.7 b	3.6 c
REG3		6.1 ab	7.3 a	6.7 ab	6.8 ab	7.2 a	6.8 ab	6.7 ab	7.4 a	7.3 a	7.5 a	7.5 a

Liking was scored on a 9-point hedonic scale; from 1 = dislike extremely to 9 = like extremely
n = cluster size
Like = the most frequently high-rated by consumers for best-liked products
Dislike = the most frequently low-rated by consuemrs for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a cluster
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a cluster

TABLE 3.5 MEAN PRODUCT LIKING OF THE FRAGRANCE STUDY

(A) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR ALL CONSUMERS AND INDIVIDUAL COMPUTER GENERATED CLUSTERS

Products		Product liking for each cluster												
		All consumers	Cluster 1				Cluster 2				Cluster3*			
			Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	
		n=321	n=82	n=120	n=54	n=128	n=79	n=97	n=43	n=142	n=51	n=87	n=34	
	Like	517/621	621	517	621	517	517	237	759	517	237	621	237/638	
	Dislike	412	196	492	492	318	318	196	318	412	412	412	196/219	
122		4.8 c	4.4 bcdefg	5.5 abcde	4.9 bcdef	5.6 abc	5.7 abcdef	5.0 bcde	5.8 ab	4.3 cde	5.6 abc	4.0 cdefg	4.9 abcde	
196		3.6 j	3.4 hi	4.4 ghi	4.1 efgh	3.3 i	4.4 hijk	2.2 k	2.3 hi	3.9 defg	3.0 ijk	3.9 defg	3.0 h	
211		5.1 ab	4.9 abcd	5.8 ab	6.0 ab	5.6 abc	6.1 a	4.5 efg	4.9 abcd	4.9 abc	4.6 defg	5.1 ab	4.4 bcdefg	
219		4.1 hi	4.3 cdefgh	4.9 efgh	4.7 cdef	4.4 gh	4.8 ghij	3.2 ij	3.5 efg	4.0 def	4.1 ghf	3.9 defgh	3.1 gh	
237		5.3 a	5.2 ab	5.7 abcd	5.2 abcd	5.8 ab	5.7 abcdef	5.9 a	6.0 a	5.1 abc	6.0 a	4.2 bcd	5.5 abc	
316		4.5 ef	4.1 cdefghi	5.2 bcdef	4.3 defg	5.3 abcdef	5.2 bcdefg	4.7 cdefg	4.5 cde	4.0 def	4.5 defg	3.4 defgh	4.3 cdefgh	
318		3.6 j	3.5 hi	4.4 ghi	2.9 ij	3.3 i	4.0 k	3.0 ijk	2.2 hi	3.9 defg	3.4 hij	3.3 efghi	3.5 fgh	
359		4.4 ef	4.4 bcdef	5.0 efg	4.6 cdefg	5.0 cdefgh	5.3 abcdefg	4.2 fgh	4.1 def	3.9 defg	4.1 fgh	4.1 cdef	4.7 abcdef	
412		3.1 k	3.5 ghi	4.1 i	2.7 ij	3.3 i	4.2 jk	2.5 jk	1.8 i	3.3 g	2.1 k	2.5 i	3.9 efgh	
420		4.3 fgh	3.4 hi	5.1 cdef	3.2 hij	4.9 defg	5.2 cdefgh	4.5 defg	4.8 bcd	4.0 def	4.7 cdef	3.3 fghi	3.9 efgh	
492		4.0 i	3.3 i	4.3 hi	2.3 j	4.4 gh	4.3 ijk	4.7 cdefg	5.2 abcd	3.7 efg	4.4 efgh	3.0 hi	4.3 cdefgh	
513		5.0 c	5.0 abc	5.7 abc	5.1 abcde	5.6 abc	5.9 abcd	5.1 abcde	5.6 ab	4.9 abc	4.9 bcdef	4.0 cdefg	5.3 abcd	
517		5.3 a	4.9 abc	5.9 a	5.5 abc	5.8 a	6.0 ab	5.3 abcd	6.0 a	5.2 a	5.7 ab	4.9 abc	5.0 abcde	
549		4.4 efg	4.6 abcde	5.0 defg	4.7 cdef	4.8 efg	5.2 cdefg	4.1 gh	3.3 fgh	4.3 cde	3.7 ghi	4.2 bcde	4.9 abcde	
621		5.3 a	5.4 a	5.8 ab	6.1 a	5.6 abc	6.0 abc	4.6 defg	4.8 bcd	5.2 a	5.2 abcde	5.7 a	3.4 gh	
638		5.1 ab	4.7 abcde	5.5 abcde	5.5 abc	5.6 abc	5.6 abcdef	5.6 ab	5.5 abc	5.0 ab	5.4 abcd	4.1 cdef	5.7 a	
715		4.8 cd	4.4 bcdef	5.2 bcdef	3.9 fgh	5.6 abc	5.4 abcdefg	4.9 bcdef	5.3 abc	4.1 def	4.6 defg	4.1 cdef	5.1 abcde	
759		4.8 c	4.0 defghi	5.0 efg	4.0 fgh	5.4 abcde	5.3 abcdefg	5.5 abc	6.0 a	4.4 bcd	5.0 abcdef	3.8 defgh	5.0 abcde	
814		4.6 de	4.0 efghi	5.1 cdef	4.5 cdefg	5.1 bcdef	5.2 defgh	4.7 defg	5.1 abcd	4.2 ed	4.7 cdef	3.9 defg	4.9 abcde	
861		4.2 ghi	4.4 bcdef	4.8 fgh	5.0 bcdef	4.7 fg	5.1 efghi	3.4 hi	3.5 efg	3.9 defg	3.7 ghi	4.3 bcd	4.2 defgh	
910		3.6 j	3.6 fghi	4.7 fghi	3.6 ghi	3.9 hi	5.0 fghi	2.8 ijk	2.8 ghi	3.5 fg	2.7 jk	3.1 ghi	3.6 fgh	
947		5.0 c	4.5 abcde	5.7 abc	5.1 abcd	5.5 abcd	5.9 abcde	5.2 abcde	5.3 abc	5.0 ab	5.1 abcdef	4.0 cdefg	5.6 ab	

Liking was scored on a 7-point hedonic scale; from 1 = dislike very much to 7 = like very much
n = cluster size
Like = the mostt frequently high-rated by consumers for best-liked products
Dislike = the most frequently low-rated by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a cluster
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a cluster

(B) MEAN CONSUMER RANK SCORES (TRANSFORMED HEDONIC SCALE) FOR ALL CONSUMERS AND INDIVIDUAL COMPUTER GENERATED CLUSTERS

Products	Product liking for each cluster												
	All consumers	Cluster 1				Cluster 2				Cluster 3			
		Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ	Complete linkage	K-means	Ward's	MCQ
	n=321	n=72	n=84	n=66	n=119	n=47	n=60	n=37	n=94	n=42	n=50	n=34	n=33
Like	517/621	237	621	517	237	621	621	621	621	237	638	715	621
Dislike	412	196	412	412	196	318/910	318	318	412	318	412	492	196
122	12.5 fe	15.6 abc	13.0 c	14.3 abcd	14.0 bcd	11.6 cde	11.9 cdefgh	12.1 cdef	12.2 defgh	9.2 def	13.7 abcde	8.7 efgh	12.0 abcde
196	8.4 j	4.8 i	7.3 def	5.0 i	6.2 j	5.9 gh	10.6 defghi	6.2 i	8.4 jkl	9.8 def	4.3 k	10.6 bcdefg	6.7 f
211	13.6 bc	10.8 fg	14.4 bc	12.2 de	11.6 def	15.9 ab	16.1 ab	14.7 abcd	16.1 ab	16.4 a	12.0 bcdef	13.6 abcd	13.9 abc
219	9.9 i	8.6 gh	9.4 d	8.8 fg	8.2 hij	7.2 fgh	9.7 fghijk	11.8 cdefg	9.1 ijk	12.1 bcde	8.0 hij	9.0 defgh	12.3 abcd
237	14.5 ab	17.1 a	17.0 ab	16.5 a	16.9 a	14.1 abcd	12.6 cdefg	14.5 abcd	13.8 abcd	16.9 a	15.5 a	15.6 a	15.2 ab
316	11.6 gh	12.5 def	13.3 c	13.1 bcde	11.8 def	14.8 abc	9.0 hijkl	9.5 efghi	13.7 bcde	8.1 fe	11.8 cdefg	14.0 abc	7.3 ef
318	8.3 j	6.3 hi	7.6 def	5.5 hi	7.3 ij	5.5 gh	6.0 l	6.2 i	6.6 kl	7.1 fe	6.0 ijk	13.1 abcde	13.7 abc
359	11.3 h	11.2 efg	9.5 d	8.8 fg	9.9 fgh	12.5 bcde	13.2 bcdef	13.7 abcde	11.4 defghi	10.1 cdef	10.3 efgh	8.7 efgh	14.9 ab
412	6.9 k	5.3 i	5.5 f	4.7 i	6.2 j	5.1 h	6.3 kl	7.8 ghi	5.7 l	7.0 f	4.7 jk	9.1 defgh	8.5 def
420	10.8 h	10.7 fg	12.5 c	10.7 ef	10.1 fgh	10.6 def	7.1 jkl	12.1 cde	10.9 efghij	9.3 def	10.4 defgh	15.1 ab	11.5 bcdef
492	9.9 i	10.1 fg	6.4 ef	14.3 abcd	9.6 fghi	9.1 efg	7.1 ijkl	5.9 i	10.1 ghij	7.8 f	15.7 a	5.6 h	13.2 abcd
513	13.4 cd	14.5 abcd	13.6 c	15.0 abcd	15.3 abc	15.9 ab	13.9 abcd	14.1 abcd	13.5 bcdef	13.1 abcd	15.5 a	13.1 abcde	12.1 abcde
517	14.7 a	14.8 abcd	16.4 ab	15.9 abc	16.5 a	15.3 ab	15.2 abc	16.6 ab	13.0 cdef	15.6 ab	15.6 a	13.5 abcd	15.3 ab
549	10.9 h	9.3 gh	9.5 d	8.4 fgh	10.5 efgh	13.7 abcd	13.6 bcde	7.8 fghi	10.8 fghij	7.7 f	8.4 ghi	10.6 bcdefg	12.4 abcd
621	14.7 a	12.6 cdef	17.4 a	14.0 abcd	12.8 de	17.1 a	17.3 a	17.4 a	16.5 a	14.3 abc	10.2 fgh	12.0 abcdef	16.6 a
638	13.7 bc	16.0 ab	14.7 abc	16.0 ab	16.3 ab	14.1 abcd	14.2 abc	15.1 abc	13.7 bcde	15.4 ab	16.8 a	13.5 abcd	9.2 cdef
715	12.3 fg	12.8 cdef	14.4 bc	12.9 cde	10.6 efg	12.8 bcd	9.7 ghijk	10.5 defgh	15.7 abc	15.1 ab	13.7 abcd	15.5 a	11.0 bcdef
759	12.5 def	15.3 abcd	12.8 c	15.0 abcd	11.8 def	11.0 de	10.2 efghij	9.6 efghi	13.9 abcd	12.9 abcd	15.8 a	11.2 abcdefg	9.7 cdef
814	11.5 gh	13.9 bcde	9.7 d	13.7 abcde	13.6 cd	10.5 def	10.4 defghij	13.4 abcde	9.4 hijk	12.9 abcd	15.3 ab	9.7 cdefgh	8.5 def
861	9.9 i	8.9 gh	8.4 def	7.2 ghi	9.2 ghi	10.9 def	12.7 bcdefg	12.4 bcde	8.9 ijk	9.0 def	6.5 ijk	6.7 hg	11.1 bcdef
910	8.4 j	6.7 hi	5.8 ef	6.8 ghi	8.3 ghij	5.5 gh	12.7 bcdefg	6.8 hi	6.9 kl	9.2 def	8.2 ih	8.3 fgh	9.4 cdef
947	13.3 cde	15.1 abcd	14.3 bc	14.3 abcd	16.2 ab	14.0 abcd	13.5 bcde	14.7 abcd	12.7 defg	14.0 abc	14.7 abc	15.9 a	8.6 def

Ranking was transfromed from 1-9 point hedonic scale to 1-22 (1 = the least like to 22 = the most like)
n = cluster size
Like = the most frequently high-ranked by consumers for best-liked products
Dislike = the most frequently low-ranked by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean ranking score of a cluster
Solid line box = the median ranking score of a cluster
Dotted line box = the lowest mean ranking score of a cluster

(C) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR INDIVIDUAL STRICT CLUSTERS

Products	Product liking for each cluster														
Like	237	237,638	237	237	517	517	517	621	621	621	621	621	638	715	759
Dislike	196	196,219	318	412	318	412	492	196	318	318,910	412	492	412	492	318
n	35	59	28	30	28	35	21	28	37	58	39	20	28	13	25
122	5.3 bcdef	5.0 bcde	5.6 abcd	5.7 abc	5.0 bcde	5.1 bcd	4.6 bcde	4.5 cde	4.5 bcdef	4.6 cde	4.7 bcd	4.9 bc	4.9 bcdef	4.5 bcd	5.4 abc
196	1.4 j	2.1 j	3.1 h	3.1 h	3.0 h	3.1 gh	3.9 cde	1.5 g	3.6 fgh	3.7 ef	3.7 def	4.2 bcd	3.3 g	5.2 abcd	2.9 efg
211	5.0 bcdefg	5.0 bcde	5.0 bcdef	4.9 bcdef	5.5 bcd	5.1 bcd	5.4 abcd	5.4 abc	5.8 ab	5.7 ab	5.5 b	5.7 ab	4.5 bcdefg	6.0 ab	5.2 bc
219	4.0 fghi	3.5 ghi	3.8 fgh	3.6 fgh	3.9 efgh	3.7 fgh	4.9 bcde	4.4 cde	4.2 defg	4.2 de	4.2 bcdef	4.7 bcd	4.1 cdefg	4.6 bcd	3.4 def
237	6.8 a	6.3 a	6.9 a	6.7 a	5.8 abc	5.9 ab	5.8 ab	5.5 abc	4.6 bcdef	4.7 bcde	4.7 bcd	5.0 abc	5.7 ab	5.4 abcd	5.6 abc
316	4.7 cdefgh	4.6 cdefg	4.8 bcdef	5.2 bcd	4.8 bcdef	5.5 abc	4.8 bcde	4.6 cde	4.5 cdef	4.6 cde	4.5 bcd	4.7 bcd	4.5 bcdefg	4.9 abcd	4.7 bcd
318	3.4 hi	3.4 hi	1.6 i	3.7 defgh	1.6 i	3.7 efgh	4.2 bcde	2.5 gf	1.5 i	2.4 g	3.0 f	3.3 cde	3.4 fg	4.4 bcd	1.5 g
359	4.4 defghi	4.4 defgh	4.7 cdefg	4.3 cdefgh	4.8 bcdef	4.9 bcdef	4.6 bcde	4.7 cde	4.9 bcde	4.9 bcd	4.8 bcd	5.1 ab	4.2 bcdefg	4.2 bcd	4.3 cde
412	3.4 hi	3.1 ij	3.5 gh	1.5 i	3.1 gh	1.4 i	3.3 ef	2.8 fg	2.8 hi	2.7 fg	1.5 g	3.0 de	1.4 h	3.6 d	2.3 fg
420	4.3 efghi	4.5 cdefg	4.4 defgh	4.4 cdefgh	4.8 bcde	4.9 bcdef	4.0 bcde	4.9 bcd	4.4 cdefg	4.4 de	4.5 bcd	3.9 bcd	4.3 bcdefg	4.5 bcd	4.5 bcd
492	3.8 ghi	3.9 fghi	3.9 efgh	3.6 efgh	4.2 defgh	4.1 defg	1.7 f	3.9 def	3.9 efgh	3.8 e	3.6 def	1.6 e	3.6 efg	1.5 e	4.2 cde
513	5.1 bcdef	5.2 bcd	5.4 bcd	5.2 bc	5.5 abcd	5.1 bcd	4.4 bcde	4.7 cde	5.2 bcd	5.0 bcd	4.3 bcde	4.1 bcd	4.7 bcdefg	4.7 bcd	5.2 bc
517	6.1 ab	5.9 ab	5.9 abc	6.2 ab	6.9 a	6.7 a	6.8 a	6.2 ab	5.5 abc	5.4 bc	5.2 bc	5.7 ab	5.6 abc	5.1 abcd	5.4 abc
549	4.2 fghi	4.4 defgh	4.3 defgh	4.6 cdefg	4.5 cdefg	4.6 cdef	4.3 bcde	4.5 cde	4.4 cdefg	4.6 cde	4.4 bcde	4.2 bcd	3.9 defg	3.7 d	3.5 def
621	5.2 bcdef	5.0 bcde	5.4 bcd	5.0 bcdef	5.8 abc	5.2 bcd	5.7 ab	6.8 a	6.8 a	6.7 a	6.8 a	6.8 a	4.7 bcdefg	5.9 abc	5.3 bc
638	5.7 abcd	5.9 ab	6.1 ab	5.6 abc	6.0 ab	5.4 abc	5.6 abc	5.2 bcd	5.3 bcd	5.0 bcd	4.9 bcd	5.7 ab	6.6 a	4.8 bcd	5.9 ab
715	5.3 bcdef	4.9 bcde	5.2 bcde	5.0 bcdef	5.3 bcd	4.8 bcdef	5.0 bcde	5.5 abc	4.9 bcde	5.0 bcd	4.9 bcd	4.7 bcd	4.4 bcdefg	6.8 a	5.6 abc
759	5.4 bcde	5.4 abcd	5.5 bcd	5.5 abc	5.6 abc	5.0 bcde	5.0 abcd	4.8 bcd	4.5 cdef	4.4 ed	4.9 bcd	5.2 ab	5.3 abcd	5.5 abcd	6.8 a
814	4.9 bcdefg	4.8 cdef	4.9 bcdef	5.0 bcde	5.3 bcd	4.9 bcdef	4.9 bcde	4.6 cde	4.6 bcdef	4.4 ed	4.5 bcd	5.0 bc	5.0 bcde	3.9 cd	5.4 abc
861	4.1 efghi	4.1 efghi	4.0 efgh	3.6 efgh	3.8 efgh	3.7 fgh	3.7 de	4.4 cde	4.1 defg	4.2 ed	3.9 cdef	4.5 bcd	3.6 efg	4.0 bcd	3.5 def
910	3.1 i	3.4 hi	3.2 h	3.2 gh	3.4 fgh	2.7 hi	4.4 bcde	3.3 ef	3.2 gh	2.5 g	3.1 ef	4.4 bcd	3.5 efg	4.2 bcd	3.4 def
947	5.9 abc	5.6 abc	5.5 abcd	5.6 abc	5.5 bcd	5.1 bcd	5.5 abc	5.0 bcd	5.2 bcd	5.0 bcd	4.7 bcd	5.5 ab	5.4 abcd	5.5 abcd	5.2 bc

Liking was scored on a 7-point hedonic scale; from 1=dislike very much to 7= like very much
n = cluster size
Like = the most frequently high-rated by consumers for best-liked products
Dislike = the most frequently low-rated by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a cluster
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a cluster

(D) MEAN CONSUMER LIKING SCORES (HEDONIC SCALE) FOR INDIVIDUAL LOOSE CLUSTERS

Products		Product liking for each cluster														
	Like	**237**	**237,638**	**237**	**237**	**517**	**517**	**517**	**621**	**621**	**621**	**621**	**621**	**638**	**715**	**759**
	Dislike	**196**	**196,219**	**318**	**412**	**318**	**412**	**492**	**196**	**318**	**318,910**	**412**	**492**	**412**	**492**	**318**
	n	101	147	87	111	85	114	74	78	95	148	123	88	110	52	79
122		5.2 bcd	5.0 bcd	5.2 bcd	5.1 bcde	5.1 bcde	5.0 bcd	4.6 defgh	4.9 bcdef	4.9 bcde	4.9 bcde	4.9 bcde	4.6 defg	5.1 bcd	4.7 bcdef	5.2 bcde
196		1.8 k	2.5 j	3.1 h	3.3 i	3.1 i	3.5 g	3.9 fghi	1.8 i	3.5 hij	3.5 hij	3.8 ghi	4.0 fgh	3.5 g	4.3 defg	3.0 j
211		4.8 cdef	4.9 cd	5.1 bcd	5.0 bcde	5.3 bc	5.1 bcd	5.3 bcd	5.2 bcd	5.5 b	5.5 b	5.4 b	5.6 ab	5.1 bcd	5.7 ab	5.3 bcd
219		3.9 ghi	3.5 hi	4.1 f	4.1 gh	4.3 efgh	4.1 efg	4.4 fgh	4.1 fg	4.3 efgh	4.3 efgh	4.2 efg	4.4 efg	4.1 fg	4.3 defg	3.7 hij
237		6.3 a	6.0 a	6.2 a	6.1 a	5.6 ab	5.5 ab	5.6 ab	5.5 ab	5.2 bcd	5.2 bcd	5.1 bc	5.3 bcd	5.5 ab	5.5 ab	5.4 abcd
316		4.7 defg	4.8 cde	4.8 cdef	4.9 cdef	4.5 defg	4.6 cdef	4.7 cdef	4.6 cdefg	4.4 defg	4.4 defg	4.6 cdef	4.7 cdef	4.8 bcdef	4.8 bcdef	4.5 defg
318		3.3 ij	3.6 ghi	2.0 i	3.7 hi	2.0 j	3.7 g	3.8 ghi	3.2 h	1.9 k	1.9 k	3.5 hi	3.5 hi	3.5 g	3.8 fg	2.0 k
359		4.5 defg	4.6 cdef	4.6 def	4.5 efg	4.5 cdefg	4.5 def	4.4 efgh	4.5 defg	4.6 cdefg	4.6 cdefg	4.5 cdef	4.3 efgh	4.6 cdef	4.4 cdef	4.6 cdef
412		3.1 j	3.1 ij	3.1 h	1.9 j	3.0 i	1.9 h	3.1 i	3.1 h	3.0 j	3.0 j	2.0 j	3.1 i	1.9 h	3.3 g	2.8 jk
420		4.4 defg	4.4 def	4.2 ef	4.6 efg	4.2 fgh	4.6 def	3.9 fghi	4.4 defg	4.0 fghi	4.0 fghi	4.3 efg	3.9 gh	4.4 def	4.1 efg	4.3 fghi
492		4.1 fgh	4.2 efg	4.1 fg	4.0 gh	4.1 gh	4.2 efg	2.1 j	3.9 gh	3.9 ghi	3.9 ghi	4.0 fgh	2.1 j	4.2 fg	2.2 h	4.4 efghi
513		5.1 bcd	5.1 bc	5.1 bcd	5.0 bcde	5.1 bcd	4.9 bcd	4.7 cdef	5.1 bcde	5.0 bcde	5.0 bcde	4.8 bcde	4.6 defg	4.9 bcde	4.9 bcde	5.1 bcde
517		5.6 ab	5.6 ab	5.7 ab	5.7 ab	6.3 a	6.2 a	6.2 a	5.4 abc	5.4 b	5.4 b	5.3 b	5.5 abc	5.5 ab	5.3 abc	5.4 abc
549		4.3 efg	4.4 def	4.2 ef	4.3 fgh	4.2 fgh	4.1 efg	4.4 efgh	4.4 defg	4.3 efgh	4.3 efgh	4.4 defg	4.5 efg	4.3 fe	4.7 bcdef	4.3 fghi
621		5.0 bcde	5.1 bc	5.5 abc	5.4 bcd	5.7 ab	5.5 ab	5.7 ab	6.3 a	6.3 a	6.3 a	6.2 a	6.3 a	5.2 bc	5.5 ab	5.1 bcde
638		5.5 bc	5.5 ab	5.8 ab	5.6 abc	5.7 ab	5.3 bc	5.6 abc	5.1 bcde	5.3 bc	5.3 bc	5.0 bcd	5.3 bcd	6.1 a	5.1 bcd	5.6 ab
715		5.0 bcde	4.9 bcd	5.1 bcd	4.9 cdef	5.0 bcdef	4.7 cde	4.5 defgh	4.7 bcdefg	4.8 bcdef	4.8 bcdef	4.6 cdef	4.5 efg	4.5 cdef	6.2 a	5.0 bcde
759		5.0 bcde	5.1 bc	5.2 bcd	5.1 bcde	5.1 bcd	5.0 bcd	4.7 defg	4.8 bcdefg	4.9 bcde	4.9 bcde	4.8 bcde	4.6 defg	5.2 bc	4.9 bcdef	6.2 a
814		4.6 defg	4.6 cdef	4.9 cde	4.8 def	4.9 bcdefg	4.6 cdef	4.4 efgh	4.6 cdefg	4.8 bcdef	4.8 bcdef	4.5 cdef	4.3 efgh	4.9 bcde	4.3 defg	5.0 bcde
861		4.0 fghi	4.0 fgh	4.1 fg	4.0 gh	4.2 fgh	4.0 fg	4.1 fgh	4.2 efg	4.3 efgh	4.3 efgh	4.0 fgh	4.3 efgh	4.0 fg	4.2 defg	4.1 ghi
910		3.4 hij	3.4 hi	3.3 gh	3.2 i	3.6 hi	3.5 g	3.8 hi	3.2 h	3.5 ij	3.5 ij	3.2 i	3.6 hi	3.5 g	3.9 fg	3.6 ij
947		5.1 bcd	5.1 bc	5.1 bcd	5.1 bcde	5.2 bcd	5.0 bcd	5.3 bcde	4.9 bcdef	5.0 bcde	5.0 bcde	4.9 bcde	5.1 bcde	5.1 bc	5.0 bcde	5.1 bcde

Liking was scored on a 7-point hedonic scale; from 1 = dislike very much to 7 = like very much
n = cluster size
Like = the most frequently high-rated by consumers for best-liked products
Dislike = the most frequently low-rated by consumers for least-liked products
Mean with the same letters in each column are not significantly different using Tukey's test at α= 0.05

Shaded box = the highest mean liking score of a clust
Solid line box = the median liking score of a cluster
Dotted line box = the lowest mean liking score of a clus

Therefore, unlike the milk study, the fragrance study's clusters obviously varied in their most frequently liked/disliked products. This occurred in part because of the clustering methods used and in part because there were several highly liked products when considering the overall study. Nine percent, 9% and 8% of consumers in the fragrance study chose 517, 621 and 237 as their highest-rated products, respectively; and 13%, 11% and 11% consumers rated 412, 196 and 318 as their lowest-rated products, respectively.

Mean Comparisons of Consumer Subgroups

Four important findings emerged from the ANOVA and mean comparisons. First, for each SPC and manual clustering method, ANOVA indicated that the interaction sample×cluster significantly ($P < 0.0001$) affected liking scores in both the milk and fragrance studies. This is logical given the fact that we conduct clustering to help determine different patterns of liking among consumers or samples. Second, mean comparisons often showed significant differences among the sample average liking scores. Again, this indicates the clustering methods are separating groups of consumers that find differences in mean liking of the products. The mean rating/ranking scores and significant differences among samples in each clustering method using Tukey-Kramer multiple comparisons are given in Table 3.4-3.5A-D.

Third, if the consumer data set is uncomplicated, product liking patterns of clusters (either from the same SPC methods or across all methods used in this study) gave the same most/least liked products 65-75% of the time, but liking patterns of products in the middle of the set varied more. For example, in the milk study it was expected that the highest (shaded box), median (solid line box), and lowest (dotted line box) mean liking scores of Cluster 1 would be in a similar order across the SPC methods (Table 3.4A-D). However, that did not occur. For example, Cluster 1 in complete linkage had rating means of REG3 > LFA2 > REG2; k-means had LFA3 > LFA0 > REG0 & REG2; Ward's had REG3 > LFA2 > REG2; and MCQ had REG3 > LFA3 > LFA0. Such data shows problems that can result when a clustering method is chosen arbitrarily ("historical use", "always done it that way", "thought we would give it a try") for a set of data.

Research or marketing strategy could be altered because the method chosen results in larger or smaller consumer clusters with differing products as the most or least liked. If the chosen clustering method yielded clusters that had similar most/least liked products, liking patterns and degrees of liking could be taken into account. The MCQ method exhibited three consumer preference clusters (Table 3.4A): 1) Cluster 1 represents consumers who moderately liked REG3 and neither disliked or liked LFA0, 2) Cluster 2 represents consumers who moderately liked REG3 and very much disliked LFA0, and 3) Cluster 3 was not clear for any liking patterns. Product developers should examine real mean scores in each cluster to determine if any clusters could be combined for designing an ideal product for the group.

If consumer data are complicated, e.g. the fragrance study, clusters (from either the same clustering methods or across all methods used in this study) tended to represent different liking patterns, even for the most/least liked products. The ranges of liking patterns among the 22 samples are shown in Table 3.5A-D. The highest (shaded box), median (solid line box), and lowest (dotted-line box) mean liking scores found for Cluster 1 are dissimilar products across the various clustering methods. SPC analyses based on rating scores yielded clusters containing products 517, 621, 237, 211, 638, 759, and 715 that had the highest mean scores. Whereas, clustering based on ranking scores yielded clusters of products 621, 237, 638, and 947 with the highest ranks. Both rating and ranking showed that products 412, 492,318, and 196 had the lowest overall scores. Products 517, 621 and 237, 638, and 211 had mean scores that were not significantly different from one another, and, thus, were located in the top five most preferred products. Product 412 was rated the least liked product ($P < 0.05$), and products 196 and 318 mean scores were the second lowest as illustrated in Table 3.5A. Because the original data had a number of most frequently liked/disliked products and the original data's mean comparisons contained many products with the same degree of liking scores (on average), the clustering results of the fragrance study exhibited more diversity in product liking patterns.

When comparing the SPCs, to loose and strict clusters it is expected that these clusters should show the same set of products as being the highest, median and lowest mean liking/ranking scores. For all clusters from both milk and fragrance studies, regardless the score type, only one cluster (Cluster 3 by complete linkage method on the rating scores of the fragrance study) resulted in the same set of products being highest, median, and lowest across the clustering methods. This suggests neither SPC based on hedonic, nor rank scores, represent the same liking pattern as the manual clusters' results. The SPC method did not account for the most/least liking pattern as much as using SPC with further manual clustering did.

Comparing Ranges of the SPC Cluster Means Versus SPC with Manual Cluster Means

For both milk and fragrance studies, the SPC plus manual segmentation gave clusters with a wider range between the low to high liking mean scores than that of SPC segmentation (Table 3.4-3.5A,C and D). In general, the liking mean range of SPC clusters is less than loose clusters and less than strict clusters. For example, in the milk study the ranges of a cluster of consumers who rated REG3 and LFA0 the most and least liked products was 5.2-7.2 (for Cluster 1 by the complete linkage method), 3.1-7.4 (loose clustering) and 2.6-7.9 (strict clustering). The SPC cluster's liking pattern indicated that when REG3 was the most frequently liked and LFA0 was the most frequently disliked products (Table 3.4A Cluster 1 Complete linkage and MCQ), consumers scored LFA0 as neither like nor dislike (5.5 or 4.6). However, but when using manual clustering (e.g. strict; Table 3.4C), scores for LFA0 in clusters that had the same most/least liked pattern (REG3/LFA0) were considerably lower (2.6 or 3.1) indicating that LFA0 was disliked moderately. Similar trends for product scores also were found in the fragrance study (Table 3.5A,C and D).

The analysis based on the ranking scores was not compared because, 1) the range of scores was dependent on the number of samples and transforming 9-point hedonic scale data to rank data gave a considerable number of ties; 2) the transformed rank scale had less meaning (what does a score of 14 mean?) than the hedonic scale; and 3) determining a most liked and least liked product was extremely variable in the transformed rank fragrance data which did not provide any comparisons. Therefore, SPC using ranking data based on transformation of hedonic data) is not recommended.

Conclusions and Recommendations

Clustering consumers using SPC based methods on either hedonic or ranking data gave inconsistent clusters of individuals and varying preferences within those clusters. A lower percentage of consumers with the same most frequently liked/disliked products were placed together in an appropriate cluster using SPC methods than using the SPC plus manual clustering methods described in this paper. If researchers' interests are focused on most frequently liked products or most frequently liked versus disliked products, SPC methods did not cluster consumers appropriately. Thus, a standard SPC procedure may not be the best method for separating consumers, or for understanding their best liking rating/ranking of products. Although the SPC methods did not group all consumers appropriately, the most frequently liked/disliked products that each SPC cluster represents could be used as a guide for additional manual clustering. Perhaps a combination of SPC and manual clustering methods may produce more homogenous clusters for researchers. Further studies are needed to determine how well these clustering combination results may be. Based on this paper, simply choosing any one clustering method for use in all studies may be inappropriate. Researchers must use various SPC methods and determine what works best for their data set and objectives.

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Chapter 4

CHAPTER 4 - Influence of Cluster Analysis on Internal and External Preference Maps

Abstract

Creating new products based on attributes selected from preference maps created using consumers with heterogeneous preferences may cause new products to fail. Unfortunately, common statistical package clustering methods may result in consumer segments that still are fairly heterogeneous. Methods for clustering that produce more homogeneous clusters have been developed. We hypothesized that ambiguity and failure in preference map interpretation can be reduced if product improvement suggestions are made from maps where the consumers have homogeneous likes and dislikes. This study observes how clusters with higher homogeneity in product liking patterns change spaces of consumer, descriptor, and product co-ordinates in internal and external preference maps. Although more improvement was exhibited for internal preference maps, the study found maps created based on more homogenous consumer clusters showed small improvements in understanding of the descriptors that promote liking for external preference maps. The complexity of the study (e.g. larger numbers of products and numerous descriptors) may contribute to a negative impact on co-ordinate spaces in external preference maps and reduce the ability to interpret data from those maps regardless of the homogeneity of the segmented consumer cluster. In all cases, the interpretations require examination of the original descriptive data from the sensory studies to make the best product suggestions.

Practical Applications

For the best interpretation of a preference map it is important to consider key findings from the original data in the descriptive study. Using maps based on overall mean liking vectors to identify attributes that drive liking or disliking is risky if the vector is not well aligned with the highest and lowest liked products, a common occurrence in this study. Researchers should not assume that clustering, even using those methods that provide more homogeneous clusters, allows them to identify positive (or negative) attributes and optimize products without first checking that the maps have not oversimplified the data.

Introduction

Preference maps have been used extensively for many types of sensory marketing and product development studies for determining drivers of liking (Tenenhaus *et al.* 2005; Delgado and Guinard 2011; Zhang *et al.* 2011), product optimization (McEwan 1996; Lovely and Meullenet 2009, Ares *et al.* 2006) and the introduction of new products into a blank space on a map (Donadini and Fumi 2010). Tenenhaus *et al.* (2005), Delgado and Guinard (2011) and Zhang *et al.* (2011) interpreted a preference map based on only it's configuration; Hein et al. (2008) brought co-ordinate values to further correlate analyses between some components' consumer scores (from the internal preference map) and descriptive attributes to help in identifying the drivers of liking; whereas, McEwan (1996), Ares *et al.* (2006) and Lovely and Meullenet (2009) used co-ordinate values from the external preference maps to calculate product optimizations. These researchers use information directly from their studies of the map coordinates to identify the drivers of liking and/or to produce projected product optimization.

But not all preference mapping is completely accurate in representing true information that can be found only in the raw data. Preference mapping assumes that data are reasonably homogeneous and multivariate techniques have not oversimplified the data. An example of relatively homogeneous data used for mapping was in Chapter 2 that reported paint data where more than 70% of consumers scored the same paint sample (code 399) as their most liked product and approximately 50% chose the same sample (code 290) as their most disliked. That paint data resulted in a rather obvious interpretation of the mapped data, even when the maps were created using different preference mapping software and methods. All maps had a high variance explained (98%) in descriptive attributes. This paint (consumer) data were reasonably homogenous in product liking patterns; this probably was a contributing factor to the production of an unambiguous preference map. If researchers could segregate consumers into clusters representing homogenous product liking/disliking, it may be reasonable to assume, as with the paint study, that a preference map from any method would produce similar results.

Statistical package cluster (SPC) analysis methods, such as Ward's (Mahanna and Lee 2010; Felberg *et al.* 2010; Sinesio *et al.* 2010; Sabbe *et al.* 2009; Childs and Drake 2009), complete linkage(Liggett *et al.* 2008), and k-means (Resano *et al.* 2009), have been applied to data sets purposely to cluster consumers together who have similar liking patterns. However, in many studies preference maps did not show clear trends because consumers are located throughout the map or in overlapping clusters (Young *et al.* 2004; Thomson *et al.* 2004; Ares *et al.* 2006; Wajrock *et al.* 2008; Endrizzi *et al.* 2010). Moreover, comparing the results from cluster analyses to the original rating (or ranking) data of each cluster, the SPC approaches did not yield: 1) clusters of consumers who had similar product liking patterns, or 2) many common consumers across the SPC methods. The clusters actually had low percentages of common consumers between SPC and manual clustering based on the highest and lowest scoring products (<40% on average of the milk study; or 22% of the fragrance study; Chapter 3).

Because preference maps often contain overlapping clusters, they may not show clear trends. Therefore, the interpretation of consumer preference in the form of cluster mean vectors is widely used (Capia *et al.* 2006; Ares *et al.* 2006; Childs and Drake 2009; Senesio *et al.* 2010; Felberg *et al.* 2010) for giving suggestions for product improvement in one direction, usually the highest liking. Those examples use cluster mean vectors rather than individual consumers to explain product preference, making the maps more visually appealing and easier to read and comprehend.

Differences in cluster liking patterns usually are reported as a group mean. However, unweighted cluster analysis depends on consumer scores for all products, which means that consumer members of the cluster often have different highest and lowest liked products (Chapter 3) even though they may have more similar liking patterns for products in the middle of the range. Unfortunately, product developers and marketers often are interested only in the highest liked products (that is what they want to sell) or the lowest liked products (determine what is wrong with the products so no mistake is made). However, assigning a new consumer to a cluster, based on the total distance (as does the hierarchical SPC), researchers could end up, “grouping consumers who like some products and disliked others with consumers who dislike all products but dislike some less than others,” (Meullenet *et al.* 2007). Ultimately this groups the wrong consumers together into the same cluster (Greenhoff and MacFie 1994).

Uncertainty in consumer liking consensus within segments causes risks in misidentifying potential market opportunities and optimizing a new product. This mis-optimized product could fall into 75-80% of the new products that did not succeed on the market (Karrh 2009). It seems reasonable to state that using standard SPC analyses alone puts researchers in jeopardy of offering a product that does not meet consumer expectations because it was optimized based on a cluster containing mixed opinions in consumer preferences (Chapter 3).

Because different SPC methods generated dissimilar clusters but manual clustering of data identified more homogenous clusters for product liking, this study was designed to determine whether the more homogeneous clusters would result in more reliable preference maps. Although preference maps are just one method for helping to identify attributes that drive liking or disliking, this study compares the influences of preference maps’ interpretation created for individual clusters. These clusters were segmented based on SPC and manual clustering to examine the possibility of obtaining the same interpretation of preference maps created by MDPREF and PLS2, as examples.

Materials and Methods

Data

Consumer and descriptive sensory studies of two product types were used: milk (Adhikari *et al.* 2010) and fragrances (Retiveau 2004). The milk and fragrance consumer studies differed in number of samples (6 and 22), number of consumers (115 and 321), numbers of descriptive attributes (21 and 56), homogeneity in sample liking among consumers (milk was more homogenous and fragrance more heterogeneous in liking patterns) and data variability (Chapter 2). Thus, the data sets represent a reasonably uncomplicated and a more complicated set, respectively.

Segmentation approaches

Consumers in each study were segmented using four approaches.

Approach 1 — Statistical package clustering method (SPC)

Four SPC analyses (complete linkage, k-means, Ward's and McQuitty similarity analysis [MCQ]) were performed on consumer data (hedonic original data and ranking scores — transformed from hedonic ratings). Based on the Cubic Clustering Criterion, pseudo-F and pseudo-t statistics and/or by visually examining a dendrogram using Ward's method, three clusters for the milk study and 11 clusters for the fragrance study, were chosen (Chapter 3). All analyses were performed with SAS version 9.2 (SAS Institute, Cary, NC, USA). The three largest clusters in each set of clusters were kept for further study.

Manual Clustering

Because this study was seeking a more homogenous pattern in product liking, the most frequently highest-rated and lowest-rated products (hereafter called the most frequently liked and disliked products) of each SPC cluster were determined and used for varying manual cluster approaches.

Approach 2 — "Strict" manual clustering (SMC)

The original consumer data were manually segregated into groups of consumers whose most frequently liked and the disliked products were the same. For example, 30 consumers who chose product A as most liked, and product B as least liked would be grouped together. Another 25 consumers who chose product A as most liked, and product C as least liked would form another cluster. Each product combination of the most frequently liked/disliked used for manual segmentation criteria was determined by each SPC cluster (Chapter 3).

Approach 3 — Statistical package clustering limited to "strict" manual clustering (SPCLS)

This approach maintains consumers in clusters only if they are common in both Approach 1 (SPC) and 2 (SMC). For example, mean values for each product were determined for the consumers in Cluster 1 from Ward's SPC to determine the highest and lowest scoring products for that cluster. Then consumers in Cluster 1 from Ward's SPC were reexamined manually to determine their individual most and least liked products. Only those consumers who were in Cluster 1 from Ward's SPC originally and had the same most liked and least liked products as the overall Wards' Cluster 1 were kept in the cluster. This SPCLS approach resulted in the most homogeneity of cluster members. This manual clustering was done for each individual cluster from each of the four SPC methods.

Approach 4 — Statistical package clustering limited to "loose" manual clustering (SPCLL)

This approach followed the same guidelines as SPCLS, but loosened the restrictions for determining each individual's most and least liked products. In SPCLL the cluster's most and least liked products only had to have either the highest/lowest score or be within one point of that highest/lowest score for an individual consumer to allow that consumer to stay in the cluster. For example, if an individual's highest scoring product was a hedonic score of 8 then products that scored either 7 or 8 by that consumer were considered as "highest". The same concept was applied to the lowest liked products. If any of those "highest" and "lowest" liked products matched the SPCLL cluster's most/least liked product (both the most and least criteria must be met), the consumer was kept in the cluster. Using the Ward's Cluster 1 example, in the SPCLL approach, those consumers whose highest or second highest (and lowest or second lowest) products matched the most or least liked products in Ward's Cluster 1, those consumers were maintained in the cluster. This method allowed consumers who might vary slightly in their preferences but generally were in line with most and least liked products to be maintained.

Preference mapping techniques

The next step was to create preference maps. Individual clustering methods with a higher number of common members among all the clusters were selected from Approach 3 (SPCLS) and Approach 4 (SPCLL) for the fragrance and milk consumer studies, respectively. In total there were 12 clusters in each approach (Table 4.1A,B). For the fragrance study the clusters were created by performing analysis on hedonic data through complete linkage (hedonic/complete linkage), hedonic/MCQ, rank/k-mean, and rank/MCQ SPC analyses; and for the milk study clusters were created through hedonic/k-mean, hedonic/ Ward's, rank/complete linkage and rank/Ward's. After the 12 clusters for each study were selected, the internal preference map (also known as multidimensional preference analysis or MDPREF) and external preference map (partial least square regression, PLS2 model) were created.

MDPREF and PLS2 using SAS version 9.2 (SAS Institute, Cary, NC, USA) were conducted and implemented for each cluster and its relevant descriptive sensory data. The mean vector for liking (based on hedonic scores) of each cluster was calculated. The mean vector co-ordinates were used to plot a map together with individual consumer, descriptor and product co-ordinates (calculated without including average liking scores). Although a study often may need more than two components to explain the data adequately, it is common to see only two dimensions used and discussed and, thus, only two components are mapped in this research.

Performance of the MDPREF and PLS2 maps for each clustering method for each approach applied to both the milk and fragrance studies were compared using variance explained (among consumers and descriptors) on the first two components, consumer map space, descriptive map space (possible for only PLS2 maps), attributes that promote liking and the number of maps with helpful or unhelpful interpretations. The determination of helpful or unhelpful interpretations of individual preference maps was based on three criteria: 1) consumers' highest and lowest liked products were in different quadrants; 2) the highest and lowest liked products were farther apart than most products; and 3) the highest and lowest liked products were in the same direction as the mean liking vector.

TABLE 4.1 PERCENATAGE OF VARIANCE EXPLAINED AMONG DESCRIPTIVE ATTRIBUTES AND AMONG CONSUMERS IN EACH CLUSTER

(A) OF THE MILK STUDY

Preference mapping technique	Variance explained in consumers					
	Score type/computer cluster method/cluster name	SPC	SPCLL	SPCLS	Highest/lowest liked products	SMC
MDPREF						
	Hedonic/k-mean/1	68	74	77	LFA3/REG0, REG2	74
	Hedonic/k-mean/2	77	85	86	REG3/LFA0	78
	Hedonic/k-mean/3	76	78	82	REG3/LFA0	78
	Hedonic/Ward's/1	81	85	88	REG3/REG2	82
	Hedonic/Ward's/2	72	89	93	REG3/LFA0	78
	Hedonic/Ward's/3	66	79	85	LFA3/LFA0	86
	Rank/complete linkage/1	68	81	84	LFA2, REG3/REG2	80
	Rank/complete linkage/2	83	83	86	REG3/LFA0, REG0	75
	Rank/complete linkage/3	65	81	90	REG2/LFA0	88
	Rank/Ward's/1	85	87	90	REG3/LFA0	78
	Rank/Ward's/2	74	81	83	LFA3, REG3/LFA0	73
	Rank/Ward's/3	72	94	96	REG3/REG2	82
PLS2						
	Hedonic/k-mean/1	47	56	58	LFA3/REG0, REG2	59
	Hedonic/k-mean/2	65	71	66	REG3/LFA0	61
	Hedonic/k-mean/3	55	58	59	REG3/LFA0	61
	Hedonic/Ward's/1	44	44	43	REG3/REG2	35
	Hedonic/Ward's/2	63	67	62	REG3/LFA0	61
	Hedonic/Ward's/3	61	74	82	LFA3/LFA0	72
	Rank/complete linkage/1	53	49	36	LFA2, REG3/REG2	35
	Rank/complete linkage/2	63	64	62	REG3/LFA0, REG0	57
	Rank/complete linkage/3	49	63	69	REG2/LFA0	79
	Rank/Ward's/1	60	63	60	REG3/LFA0	61
	Rank/Ward's/2	64	66	70	LFA3, REG3/LFA0	64
	Rank/Ward's/3	44	39	43	REG3/REG2	35
	Variance explained in descriptive attributes					
	Score type/computer cluster method/cluster name	**SPC**	**SPCLL**	**SPCLS**	**Highest/lowest liked products**	**SMC**
PLS2						
	Hedonic/k-mean/1	85	85	85	LFA3/REG0, REG2	85
	Hedonic/k-mean/2	86	85	86	REG3/LFA0	85
	Hedonic/k-mean/3	85	85	85	REG3/LFA0	85
	Hedonic/Ward's/1	85	84	83	REG3/REG2	81
	Hedonic/Ward's/2	86	85	84	REG3/LFA0	85
	Hedonic/Ward's/3	86	82	82	LFA3/LFA0	83
	Rank/complete linkage/1	86	85	84	LFA2, REG3/REG2	84
	Rank/complete linkage/2	86	85	86	REG3/LFA0, REG0	85
	Rank/complete linkage/3	85	86	85	REG2/LFA0	86
	Rank/Ward's/1	85	85	84	REG3/LFA0	85
	Rank/Ward's/2	86	85	85	LFA3, REG3/LFA0	85
	Rank/Ward's/3	85	84	83	REG3/REG2	81

SPC = computer clustering method (Approach 1)
SPCLL = computerized clustering and limited to loose manual cluster (Approach 4)
SPCLS = computer clustering and limited to strict manual cluster (Approach 3)
SMC = strict manual clustering method (Approach 2)
Highest liked products were the products most frequently high-rated (or ranked) by consumers
Lowest liked products were the products most frequently low-rated (or ranked) by consumers

(B) OF THE FRAGRANCE STUDY

Preference mapping technique	Variance explained in consumers					
	Score type/computer cluster method/cluster name	SPC	SPCLL	SPCLS	Highest/lowest liked products	SMC
MDPREF						
	Hedonic/complete linkage/1	32	49	64	621/196	51
	Hedonic/complete linkage/2	36	49	61	517/318	55
	Hedonic/complete linkage/3	48	54	63	237/412	53
	Hedonic/complete linkage/4	43	67	81	715/412	51
	Hedonic/MCQ/1	27	41	64	517/412	51
	Hedonic/MCQ/2	44	55	63	517/318	55
	Rank/k-mean/1	44	55	60	621/412	45
	Rank/k-mean/2	37	50	60	621/318	47
	Rank/k-mean/3	53	58	65	638/412	48
	Rank/MCQ/1	43	50	59	237/196	53
	Rank/MCQ/2	37	44	55	621/412	45
	Rank/MCQ/3	42	62	80	621/196	51
PLS2						
	Hedonic/complete linkage/1	15	30	40	621/196	34
	Hedonic/complete linkage/2	17	29	37	517/318	29
	Hedonic/complete linkage/3	24	28	41	237/412	36
	Hedonic/complete linkage/4	22	31	47	715/412	32
	Hedonic/MCQ/1	15	19	36	517/412	30
	Hedonic/MCQ/2	22	31	37	517/318	29
	Rank/k-mean/1	26	32	32	621/412	23
	Rank/k-mean/2	21	29	38	621/318	27
	Rank/k-mean/3	32	37	37	638/412	34
	Rank/MCQ/1	22	32	37	237/196	32
	Rank/MCQ/2	20	24	28	621/412	23
	Rank/MCQ/3	18	25	42	621/196	34
	% Variance explained in descriptive attributes					
	Score type/computer cluster method/cluster name	SPC	SPCLL	SPCLS	Highest/lowest liked products	SMC
PLS2						
	Hedonic/complete linkage/1	44	31	29	517/318	40
	Hedonic/complete linkage/2	43	32	32	237/412	35
	Hedonic/complete linkage/3	43	42	28	715/412	44
	Hedonic/complete linkage/4	44	44	43	621/196	26
	Hedonic/MCQ/1	45	43	38	517/318	40
	Hedonic/MCQ/2	43	37	36	517/412	43
	Rank/k-mean/1	38	39	40	621/318	37
	Rank/k-mean/2	40	35	33	621/412	42
	Rank/k-mean/3	44	40	40	638/412	29
	Rank/MCQ/1	44	40	39	237/196	38
	Rank/MCQ/2	44	43	43	621/412	42
	Rank/MCQ/3	44	39	35	621/196	26

SPC = computer clustering method (Approach 1)
SPCLL = computerized clustering and limited to loose manual cluster (Approach 4)
SPCLS = computer clustering and limited to strict manual cluster (Approach 3)
SMC = strict manual clustering method (Approach 2)
Highest liked products were the products most frequently high-rated (or ranked) by consumers
Lowest liked products were the products most frequently low-rated (or ranked) by consumers

Results

Variance explained on the first 2 components

Variance explained among consumers

In Table 4.1A, the first two components of the MDPREF maps yield the explained variance among consumers for 61% (all consumers), 65-85% (SPC), 74-94% (SPCLL), 73-88% (SMC), and 77-96% (SPCLS) for the milk study. Variance explained was 29% (all consumers), 27-53% (SPC), 41-67% (SPCLL), 45-55% (SMC), and 55-81% (SPCLS) for the fragrance study (Table 4.1B). These results show the percent of average explained variance across all clusters was lowest for SPC, next lowest for SMC, next for SPCLL, and highest for SPCLS for both the milk and fragrance studies. However, the average variance explained for the milk study increased only 14% from SPC (73% average explained) to SPCLS (87% explained), but for the fragrance study the increase was almost 25% (from 41-65% explained). One assumption is that the increase in the percent explained variance with the first two components could indicate better quality MDPREF preference maps when using SPCLS.

The first two components of the PLS2 maps account for explained variance of 53% (all consumers), 44-65% (SPC), 39-74% (SPCLL), 35-79% (SMC) and 36-82% (SPCLS) for clusters in the milk study, and 17% (all consumers), 15-32% (SPC), 19-37% (SPCLL), 23-36 % (SMC), and 28-47% (SPCLS) for clusters in the fragrance study (Table 4.1A,B). In this case when using PLS2 preference mapping, clustering using SPCLL gave the highest percent variance explained for the milk study and SPCLS, again, gave the highest average percent explained for the fragrance study, but in both cases the increase in improvement from SPC was smaller than for MDPREF, 4% for milk and 17% for fragrance.

Although it is impossible to know the exact reasons for the milk data showing smaller increases with manual clustering than the fragrance data, it is reasonable to assume that it is because the data set for milk was more homogeneous than the fragrance data. In the milk study, 52% of all consumers already liked the same product the most and 36% disliked the same product, whereas, in the fragrance study the three most liked products and the three least liked products only account for 10% of all consumers.

In addition, the highest average percent explained of the SPCLS clusters from PLS2 maps were influenced by the higher homogeneity of liking patterns of the SPCLS than SPC, SMC, and SPCLL clusters. Dissimilarities of the liking patterns' homogeneity among these four clusters are explained by their possible outcomes of having different liking patterns in each cluster. Consumers evaluated six products in the milk study. For a SPC cluster, the qualification of being a member of this group is the total differences (e.g. the squared Euclidean distance to the group's center mean in Ward's method) that consumers used in describing their liking. No specific product liking is required; therefore, according to mathematical theory any of the 720 potential liking patterns for the milk study could be a member of the SPC cluster if that member had the smallest total difference of the SPC method. Whereas, as projected by mathematical theory, there will be 24 liking patterns for the MSC clusters, 24 patterns with the total difference restriction for the SPCLS cluster and 96 patterns with the total difference limitation for the SPCLL cluster. In the case of the fragrance study, there were 1.1×10^{21}, 9.7×10^{18} (with restriction), 2.4×10^{18} and 2.4×10^{18} (with restriction) possible liking patterns for the SPC, SPCLL, SMC and SPCLS clusters. These numbers obviously show that, 1) the milk study had less liking patterns to be clustered than the fragrance study before screening consumers through the total difference criteria, i.e., data of the milk study were more homogeneous; and 2) the homogeneity was highest for SPCLS, next highest for SMC, next for SPCLL and lowest for SPC clusters in the milk and fragrance studies.

Among the complete linkage, k-means, Ward's and MCQ clustering methods used in this study, no one method necessarily is better than any other because members in each Cluster 1, 2 or 3 were so different (Chapter 3). Consequently, the clusters' product liking patterns may be the same in some clusters, but the individual people in those clusters may be different according to the SPC method used (i.e. each cluster contained less than 40% of consumers who rated, e.g., product A the highest-rated and product B the lowest-rated; Chapter 3). These results depended on which SPC method was chosen initially, although, the results also may vary depending on the data set.

Variance explained in descriptive attributes

The first two components of the PLS2 maps account for the explained variance among descriptive attributes for 86% (all consumers), 85-86% (SPC), 82-86% (SPCLL), 81-86% (SMC) and 82-86% (SPCLS) in the milk study, and 44% (all consumers), 38-45% (SPC), 31-44% (SPCLL), 26-44 % (SMC) and 28-43% (SPCLS) in the fragrance study (Table 4.1A,B). The average percent explained variation across all clusters was almost equal for both the milk and fragrance studies. The percentages tend to be equal to, or a little less than, those of the original preference map created based on all consumers. This finding may not be surprising considering that external preference mapping depends strongly on the initial mapping of the descriptive attributes and the consumer data only serves as an overlay to that data. Thus, the descriptive data, which does not vary among the clusters, rather than the consumer data, which varies considerably, appears to be driving the external preference maps.

Consumer map space

For MDPREF, the SPC spreads consumers over all four quadrants of the map, whereas the SPCLL, SMC and SPCLS maps present consumers within only two map quadrants (e.g. Fig 4.1 and supplementary results to Chapter 4A,B). The consumer spaces from SPCLL and SPCLS clusters in many maps are distributed within similar graphical confines. Both of those maps show consumers allocated within narrower areas than SMC and SPC maps. The maps from PLS2 technique also fall in the same trend for consumer spaces (supplementary results to Chapter 4C,D). In general, the SPCLL, SMC and SPCLS maps are more easily viewed and understood than the SPC maps because the consumer members are more homogenous in liking than cluster members from the SPC method. The SPCLL, SMC and SPCLS maps well represented a cluster of consumers who had the same best and least liked products. The SPCLS cluster members were more homogeneous than SPCLL and SMC in their overall liking among all products, not just their highest and lowest liked products.

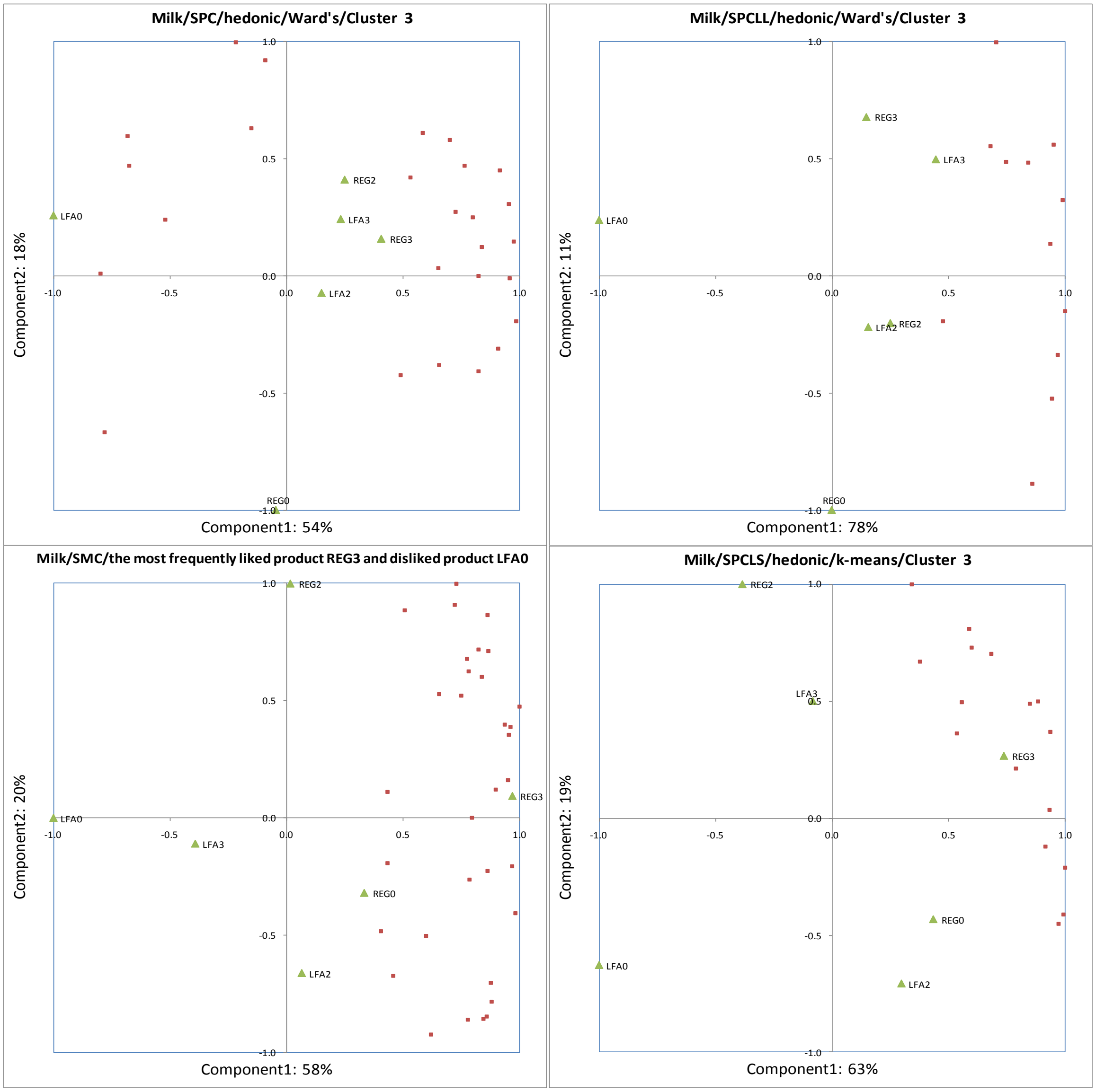

FIG. 4.1 BIPLOTS SHOWING COMPARISONS OF CONSUMER SPACES IN SPC, SPCLL, SMC AND SPCLS FROM WARD'S METHOD: CLUSTER 3 OF THE MILK STUDY

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

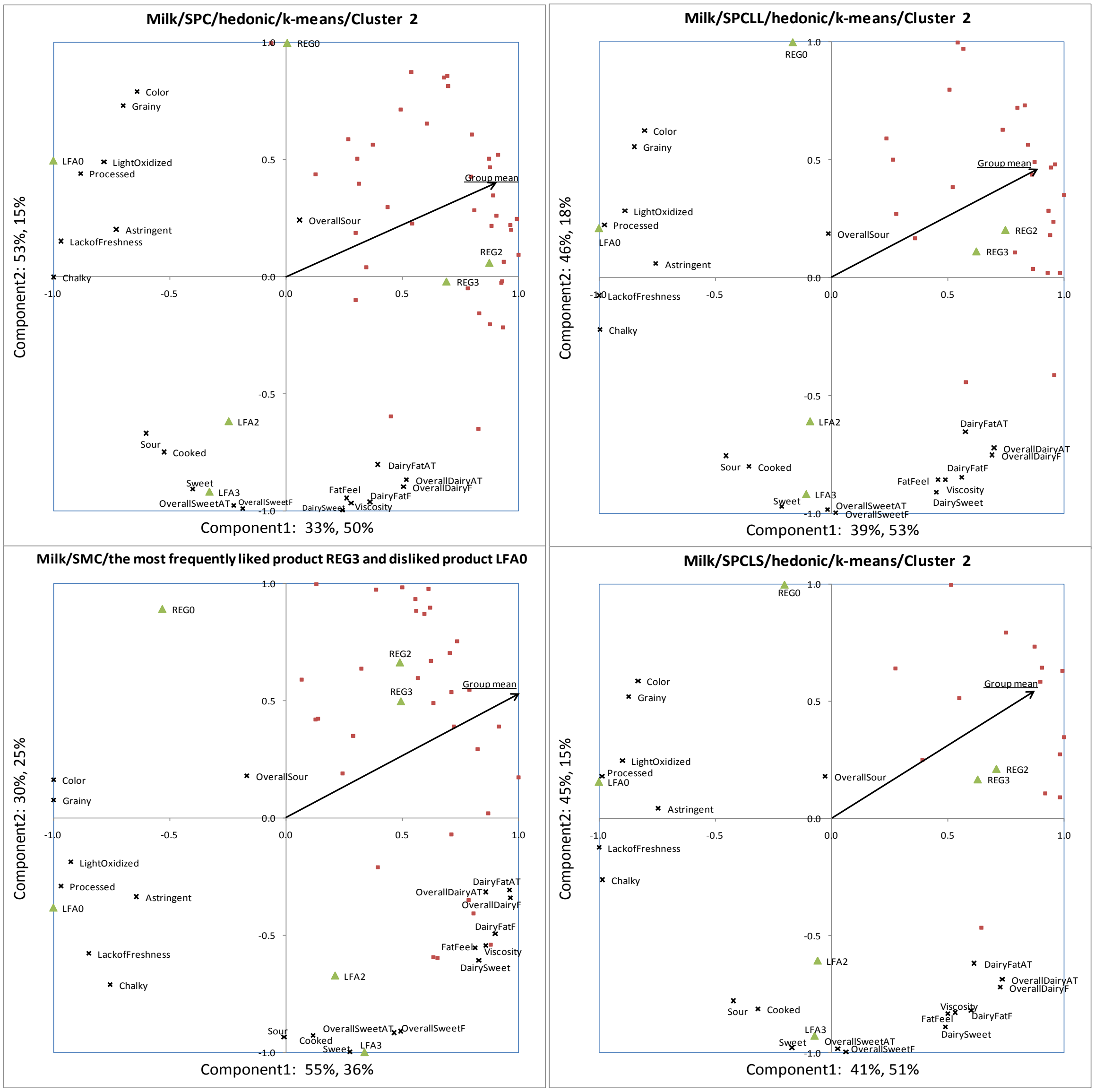

FIG. 4.2 BIPLOTS SHOWING COMPARISONS OF CONSUMER SPACES IN SPC, SPCLL, SMC AND SPCLS FROM WARD'S METHOD: CLUSTER 3 OF THE MILK STUDY

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

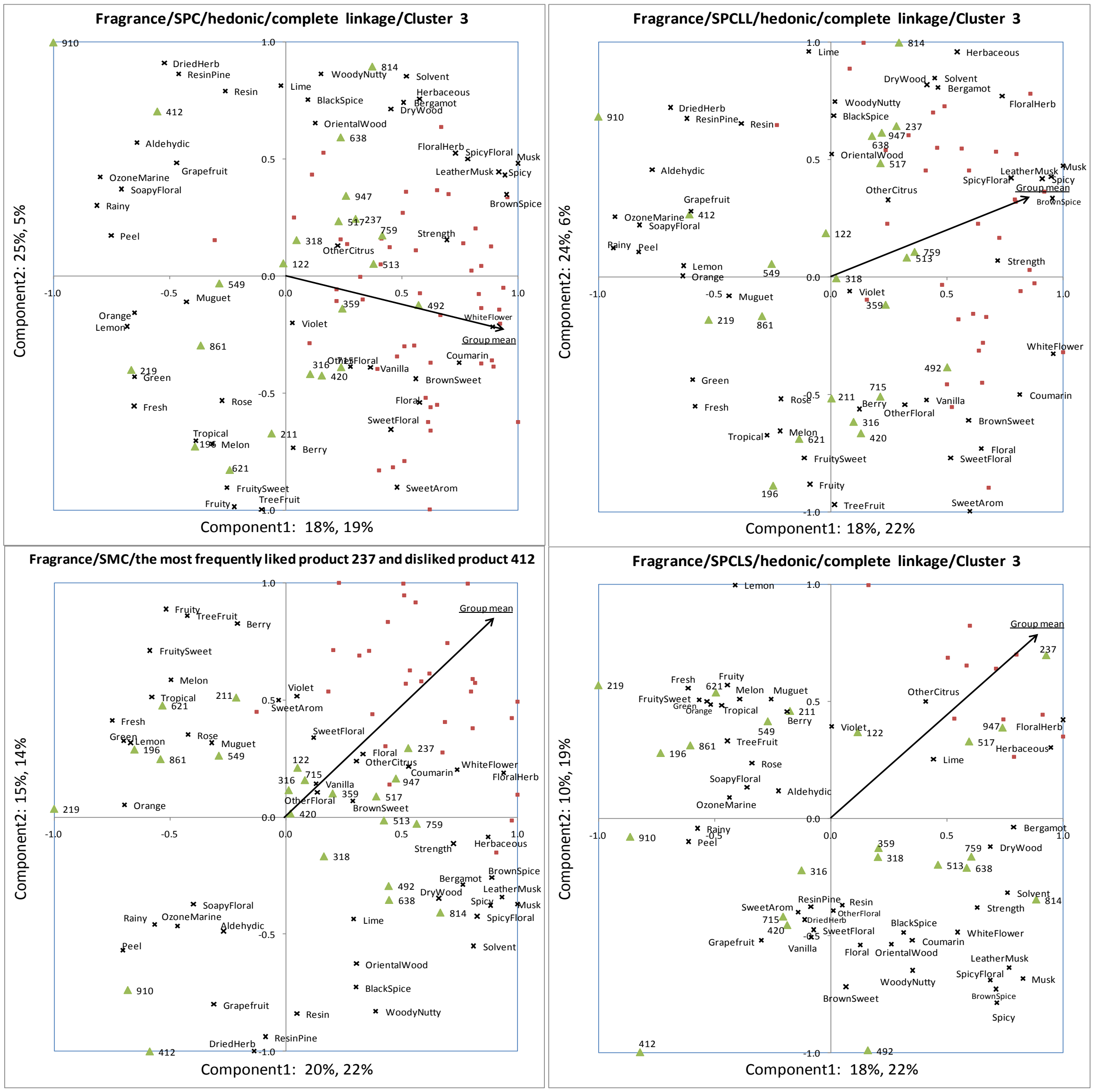

FIG. 4.3 PLS2 BIPLOTS (FROM COMPLETE LINKAGE CLUSTERING: CLUSTER 3 OF THE FRAGRANCE STUDY) SHOWING DESCRIPTIVE ATTRIBUTES RELATIVE TO FRAGRANCE PRODUCTS THAT CONTAIN INCORRECT CHARACTERISTICS REPRESENTED IN SOME PRODUCTS

Descriptive map space

The map spaces of attributes and products were not changed if the original data were uncomplicated. The milk study has six products and 21 descriptive attributes. With high percent explained variance (81-86%), all maps of SPC, SPCLL, SMC, and SPCLS clusters generally position products, and their relative attributes, in the same orientation (Fig. 4.2, see also supplementary results to Chapter 4C). On the contrary, the fragrance study has 22 samples and 56 attributes. Moreover, all maps have the percent explained variances in low percentages (26-44%; see also supplementary results to Chapter 4D). Therefore, the positions of products and their relative attributes in the SPC, SPCLL, SMC, and SPCLS maps are not always similar (Fig. 4.3), and not all attributes in the map were correctly represented by products nearby.

Intuitively, a preference map should at least show correct characteristics (high or low intensities) of the best and least liked product. Examples of this can be seen in preference maps of hedonic/complete linkage method/Cluster 3 for SPC, SPCLL, SMC, and SPCLS clusters illustrated in Fig. 4.3. Based on the original descriptive data, product 412 was rated high in woody/nutty and oriental wood attributes, whereas product 237 was rated high for floral/herb, herbaceous and aldehydic attribute. These product vectors were located close to their relevant high rated attribute vectors. One exception is the aldehydic vector in the SPC, SPCLL, and SPCLS maps that was more closely aligned to product 412 more than product 237. Therefore the SPC, SPCLL, and SPCLS maps were visually misleading because product 237 had a higher intensity of the aldehydic attributes. Product 237's vector should be aligned closely (smaller degree angle; Carr *et al.* 2009) to the aldehydic vector to illustrate its stronger intensity. Thus the SPCLS had better representation of the descriptive space in relation to the best and least liked products of Cluster 3. In the comparison of the 12 sets of SPC, SPCLL, SMC and SPCLS maps, the SPCLS maps had two visually misleading maps, but the SPC, SPCLL and SMC maps had even more visually misleading maps. All four approaches yielded visually misleading maps. Even though the SPCLS had fewer mistakes than the others, none of them did a very good job of explaining the complete relationships when comparing products and their relative attributes in a map to the original descriptive sensory data.

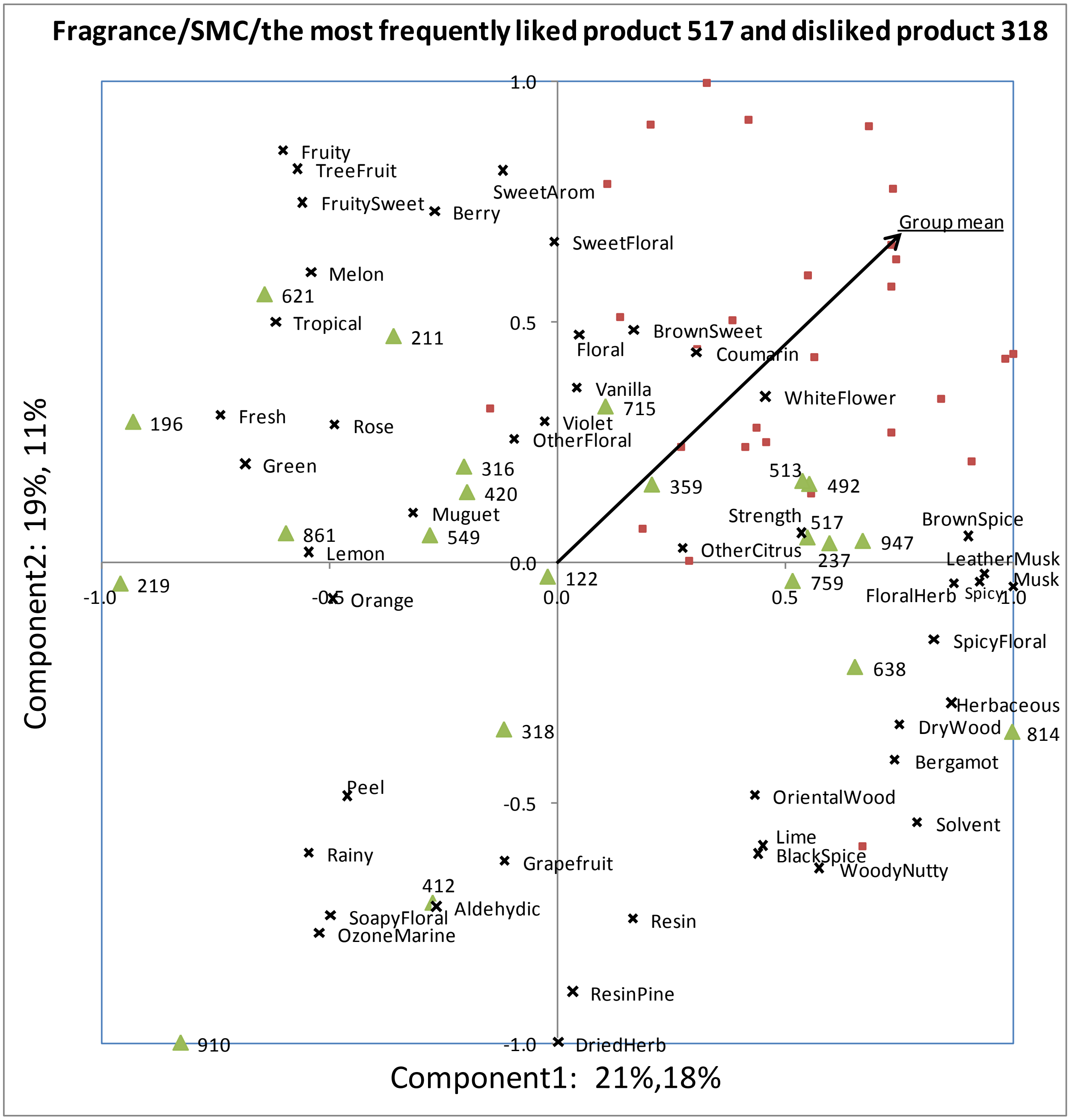

FIG. 4.4 AN EXAMPLE OF A BIPLOT THAT IS DIFFICULT TO IDENTIFY THE HIGEST LIKED PRODUCT AND POSITIVE AND NEGATIVE LIKING ATTRIBUTES

TABLE 4.2 POSITIVE AND NEGATIVE ATTRIBUTES OF EACH CLUSTER

(A) IN THE MILK STUDY

Score type/computer cluster method/cluster name	The most frequency liked/disliked products	Positive liking attributes			Negative liking attributes		
		SPC	SPCLS	SMC	SPC	SPCLS	SMC
Hedonic/k-mean/1	LFA3/REG0, REG2	Cooked, sour, sweet	Cooked, sour, sweet	Cooked, sour, sweet	Overall sour	Overall sour	Overall sour
Hedonic/k-mean/2	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?	Astringent?, light oxidized?, process?, sour?	Astringent, lack of freshness
Hedonic/k-mean/3	REG3/LFA0	—	—	—	Astringent, chalky, lack of freshness, light oxidized, processed	Astringent, chalky?, lack of freshness, light oxidized?, processed?	Astringent, lack of freshness
Hedonic/Ward's/1	REG3/REG2	Cooked, sour, sweet	Astringent, chalky, lack of freshness	Astringent?, chalky?, lack of freshness?	Overall sour	—	—
Hedonic/Ward's/2	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?	Chalky?, cooked?, sour?	Astringent, lack of freshness
Hedonic/Ward's/3	LFA3/LFA0	—	—	—	Astringent, grainy, light oxidized, processed	Astringent, light oxidized, overall sour, processed	Astringent?, color?, grainy?, overall sour
Rank/complete linkage/1	LFA2, REG3/REG2	Cooked, sour, sweet	Cooked, sour, sweet?	Cooked, sour	Overall sour	Overall sour	Overall sour
Rank/complete linkage/2	REG3/LFA0, REG0	—	—	—	Chalky?, cooked?, sour?	Chalky?, cooked?, lack of freshness?, sour?	Astringent, chalky, lack of freshness, light oxidized, processed?
Rank/complete linkage/3	REG2/LFA0	—	—	—	Astringent, chalky, lack of freshness, processed?	Astringent, chalky, lack of freshness, light oxidized?, processed?	Astringent?, chalky, lack of freshness
Rank/Ward's/1	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?, sweet?	Chalky?, cooked?, sour?	Astringent, lack of freshness
Rank/Ward's/2	LFA3, REG3/LFA0	Dairy	Dairy	—	Color, grainy	Color, grainy, light oxidized, processed?	Astringent, lack of freshness
Rank/Ward's/3	REG3/REG2	Color, grainy, light oxidized, process?	Astringent, chalky, lack of freshness	Astringent?, chalky?, lack of freshness?	Dairy	—	—

SPC = computer clustering method (Approach 1)
SPCLS = computer clustering and limited to strict manual clusters (Approach 3)
SMC = strict manual clustering method (Approach 2)

The most frequency liked products w ere the products most frequently high-rated (or ranked) by consumers
The most frequency disliked products w ere the products most frequently low -rated (or ranked) by consumers
? Represents a maybe positive (or negative) liking attribute

(B) IN THE FRAGRANCE STUDY

Score type/computer cluster method/cluster name	The most frequency liked/disliked products	Positive liking attributes			Negative liking attributes		
		SPC	SPCLS	SMC	SPC	SPCLS	MSC
Hedonic/k-mean/1	LFA3/REG0, REG2	Cooked, sour, sweet	Cooked, sour, sweet	Cooked, sour, sweet	Overall sour	Overall sour	Overall sour
Hedonic/k-mean/2	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?	Astringent?, light oxidized?, process?, sour?	Astringent, lack of freshness
Hedonic/k-mean/3	REG3/LFA0	—	—	—	Astringent, chalky, lack of freshness, light oxidized, processed	Astringent, chalky?, lack of freshness, light oxidized?, processed?	Astringent, lack of freshness
Hedonic/Ward's/1	REG3/REG2	Cooked, sour, sweet	Astringent, chalky, lack of freshness	Astringent?, chalky?, lack of freshness?	Overall sour	—	—
Hedonic/Ward's/2	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?	Chalky?, cooked?, sour?	Astringent, lack of freshness
Hedonic/Ward's/3	LFA3/LFA0	—	—	—	Astringent, grainy, light oxidized, processed	Astringent, light oxidized, overall sour, processed	Astringent?, color?, grainy?, overall sour
Rank/complete linkage/1	LFA2, REG3/REG2	Cooked, sour, sweet	Cooked, sour, sweet?	Cooked, sour	Overall sour	Overall sour	Overall sour
Rank/complete linkage/2	REG3/LFA0, REG0	—	—	—	Chalky?, cooked?, sour?	Chalky?, cooked?, lack of freshness?, sour?	Astringent, chalky, lack of freshness, light oxidized, processed?
Rank/complete linkage/3	REG2/LFA0	—	—	—	Astringent, chalky, lack of freshness, processed?	Astringent, chalky, lack of freshness, light oxidized?, processed?	Astringent?, chalky, lack of freshness
Rank/Ward's/1	REG3/LFA0	—	—	—	Chalky?, cooked?, sour?, sweet?	Chalky?, cooked?, sour?	Astringent, lack of freshness
Rank/Ward's/2	LFA3, REG3/LFA0	Dairy	Dairy	—	Color, grainy	Color, grainy, light oxidized, processed?	Astringent, lack of freshness
Rank/Ward's/3	REG3/REG2	Color, grainy, light oxidized, process?	Astringent, chalky, lack of freshness	Astringent?, chalky?, lack of freshness?	Dairy	—	—

SPC = computer clustering method (Approach 1)
SPCLS = computer clustering and limited to strict manual clusters (Approach 3)
SMC = strict manual clustering method (Approach 2)

The most frequency liked products were the products most frequently high-rated (or ranked) by consumers
The most frequency disliked products were the products most frequently low-rated (or ranked) by consumers
? Represents a maybe positive (or negative) liking attribute

Attributes that promote liking (mean vector)

Because a preference map may contain many descriptive attributes and samples, it is hard to identify the most liked product and attributes that promote and reduce liking, even though the consumers are spread in only one quadrant (Fig. 4.4). Incorporation of a mean vector in the analysis does not necessarily assist in identifying the attributes that promote liking or disliking relative to the mean vector in the preference maps. For illustration a comparison of descriptors that promote liking via the mean vectors, focusing on the PLS2 maps using SPC, SMC and SPCLS clusters for the milk study (Table 4.2A), and SPC, SPCLL and SMC for the fragrance study (Table 4.2B) was done. For the milk study, the positive attributes that drive consumers in the largest cluster (called Cluster 1) are:

1) cooked, sour and sweet for SPC, SMC and SPCLS clusters [hedonic/k-means method];

2) cooked, sour and sweet for the SPC cluster; astringent, chalky and lack of freshness for the SMC and SPCLS clusters [hedonic/ Ward's method];

3) cooked, sour and sweet for the SPC and SPCLS clusters; cooked and sour for the SMC cluster [rank/complete linkage method]; and

4) un-identified positive attributes for SPC, SMC and SPCLS clusters [rank/ Ward's method].

These positive liking attributes are similar across SPC, SMC and SPCLS Cluster 1 within clustering methods (hedonic/k-mean, rank/complete linkage and rank/Ward's method), except SPC's positive liking attributes of the hedonic/Ward's method were different from SPCLS and SMC.

The negative attributes that suppress consumer liking in Cluster 1 are:

1) overall sour for SPC, SMC and SPCLS cluster [hedonic/k-mean method];

2) overall sour for the SPC cluster; non-identified negative attribute for the SMC and SPCLS clusters [hedonic/ Ward's method];

3) overall sour for the SPC, SMC and SPCLS clusters [rank/ complete linkage method]; and

4) chalky, cooked, sour and sweet for SPC cluster; astringent and lack of freshness for SMC clusters; chalky, cooked and sour for SPCLS cluster [rank/Ward's method].

These negative liking attributes of the SPC, SMC and SPCLS for Cluster 1 were similar, except that the SPC's negative liking attributes using the hedonic/Ward's and rank/Ward's methods were different from SMC and SPCLS.

For smaller clusters, i.e., Clusters 2, 3 and so on, no positive attribute and negative attribute was similar. Results from the fragrance study also illustrated the same trend as the findings from the milk study. Therefore, clustering methods do not necessarily give the same attributes that promote liking when identified on maps using mean vectors. For the largest cluster, positive (or negative) attributes were similar most of the time. For other groups, no positive-attribute nor negative attribute was similar across cluster types.

Many of the PLS2 maps did not position the highest and lowest liked products as relevant to the direction of the mean liking vectors, e.g., Fig. 4.5. Moreover, the co-ordinate of the mean liking vectors were not always near the highest (or lowest) liked products (Fig. 4.6), especially when consumers in a cluster were not homogenous in liking patterns. Therefore, identifying the positive and negative attribute according to the mean liking vector is less reliable than using the attributes relevant to the most frequently liked (or disliked) products from a homogeneous cluster. For example, if defining positive and negative attributes based on relevance to the most frequently liked product in the milk study (REG3), the positive attributes include all the fatty-related attributes, and the negative attributes include astringent, chalky and lack of freshness (Fig. 4.7). Whereas, if positive and negative attributes are determined based on the nearest attribute vectors to the mean vector, the positive attributes are astringent, chalky and lack of freshness, and there are no identifiable negative attributes. This demonstrates a conflict with the descriptive data. REG3 was the most frequently liked product, and had high intensities for all fatty-related attributes.

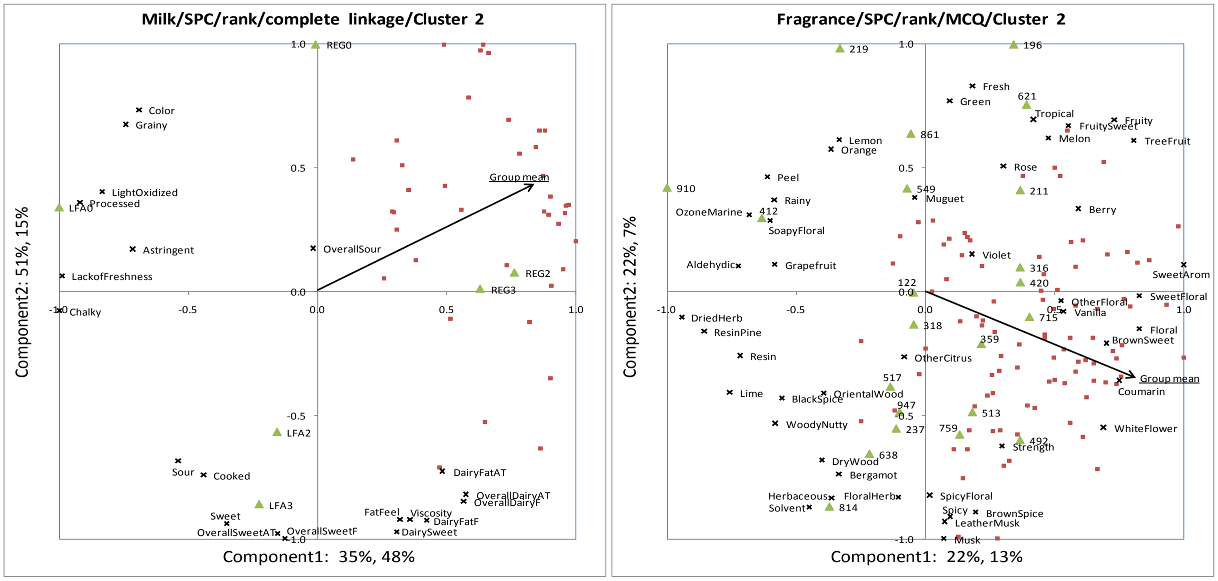

FIG. 4.5 EXAMPLES OF BIPLOTS THAT DO NOT LOCATE THE HIGHEST AND LOWEST LIKED PRODUCTS RELEVANT TO DIRECTIONS OF THE MEAN LIKING VECTORS

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

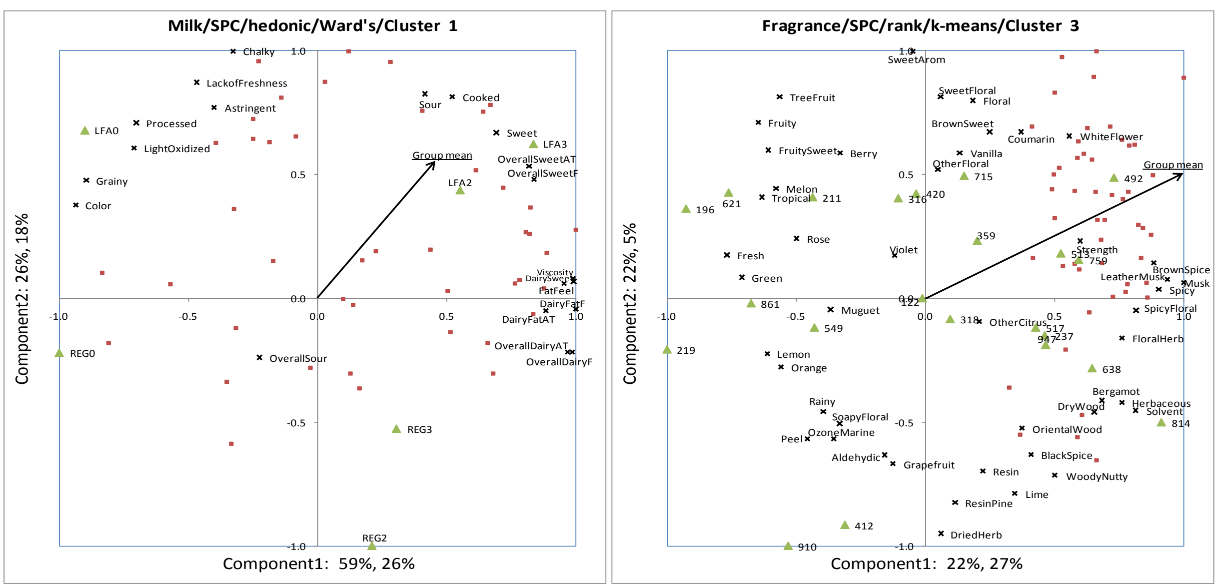

FIG. 4.6 EXAMPLES OF BIPLOTS THAT DO NOT ALLIGN THE MEAN LIKING VECTORS NEAR THE HIGHEST AND LOWEST LIKED PRODUCTS

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

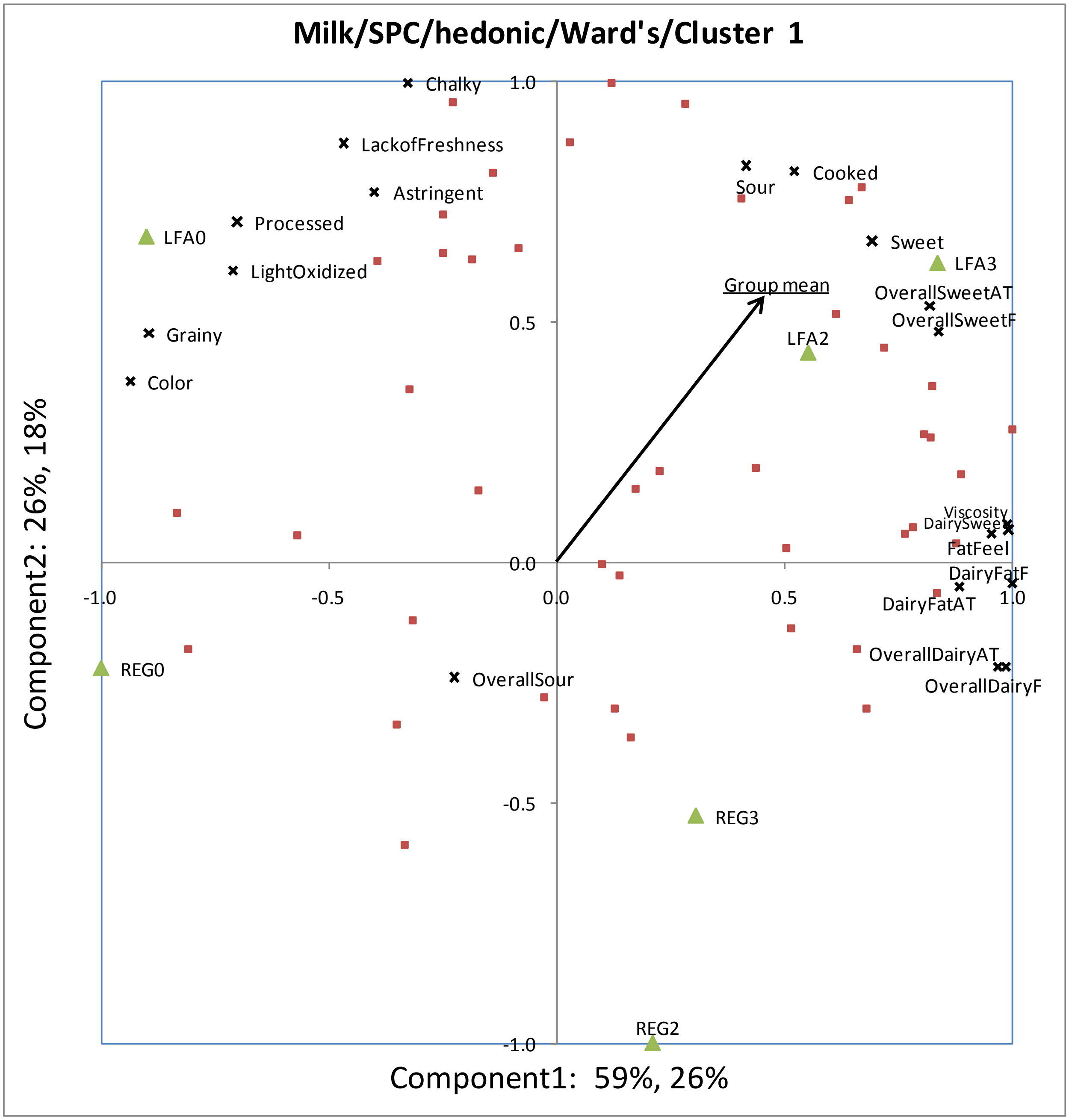

FIG. 4.7 EXAMPLE OF A PLS2 MAP FROM PERFORMING WARD'S METHOD ON THE MILK STUDY: CLUSTER 1(CLUSTERS 2 AND 3 NOT SHOWN)
[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

These results show that visually defining the positive attributes based on the attribute vectors located near the group mean vector was misleading. Therefore, using the mean liking vector as a visual prompt cannot be recommended. Neither Johansen *et al.* (2010) nor Wajrock *et al.* (2008) suggested using average liking in preference mapping.

Helpful or Unhelpful Interpretation of Individual Preference Maps Created According to Individual Clusters

To determine if each preference map of an individual cluster represents helpful or unhelpful interpretation, the three criteria explained in the material and method section were used and a map that meets these criteria is considered a helpful map. For an example of the three criteria, Fig. 4.8 has the highest liked product (REG3) and the lowest liked product (LFA0) located in different quadrants (meet criteria 1). However, REG3 was not farther apart from LFA0 than from most other products, and those two products were not in the direction of the mean liking vector (not meet criteria 2 and 3). Therefore, Fig. 4.8 is defined as an unhelpful map because it does not meet all the criteria needed to visually use the map by people with little other access to the data. The complete results are reported in Table 4.3.

Across all approaches and based on only the three criteria, the milk study's clusters resulted from performing k-means method on hedonic scores and from performing complete linkage method on rank scores these methods gave the highest number of helpful maps (five out of 12; Table 4.3). For the fragrance study, clusters from the complete linkage analysis on hedonic scores results yielded the best three helpful maps (out of 12).

Across the combinations of data types and SPC methods used in this study, the number of helpful maps for the milk study are: two (out of 12), two (out of 12), two (out of nine) and three (out of 12) for SPC, SPCLL, SMC and SPCLS, respectively. For the fragrance study they are: zero (out of 11), zero (out of 11), two (out of eight) and four (out of 11) for SPC, SPCLL, SMC and SPCLS, respectively (Table 4.3). Plotting individual PLS2 maps for each cluster was not as helpful when interpreting directly from the map space.

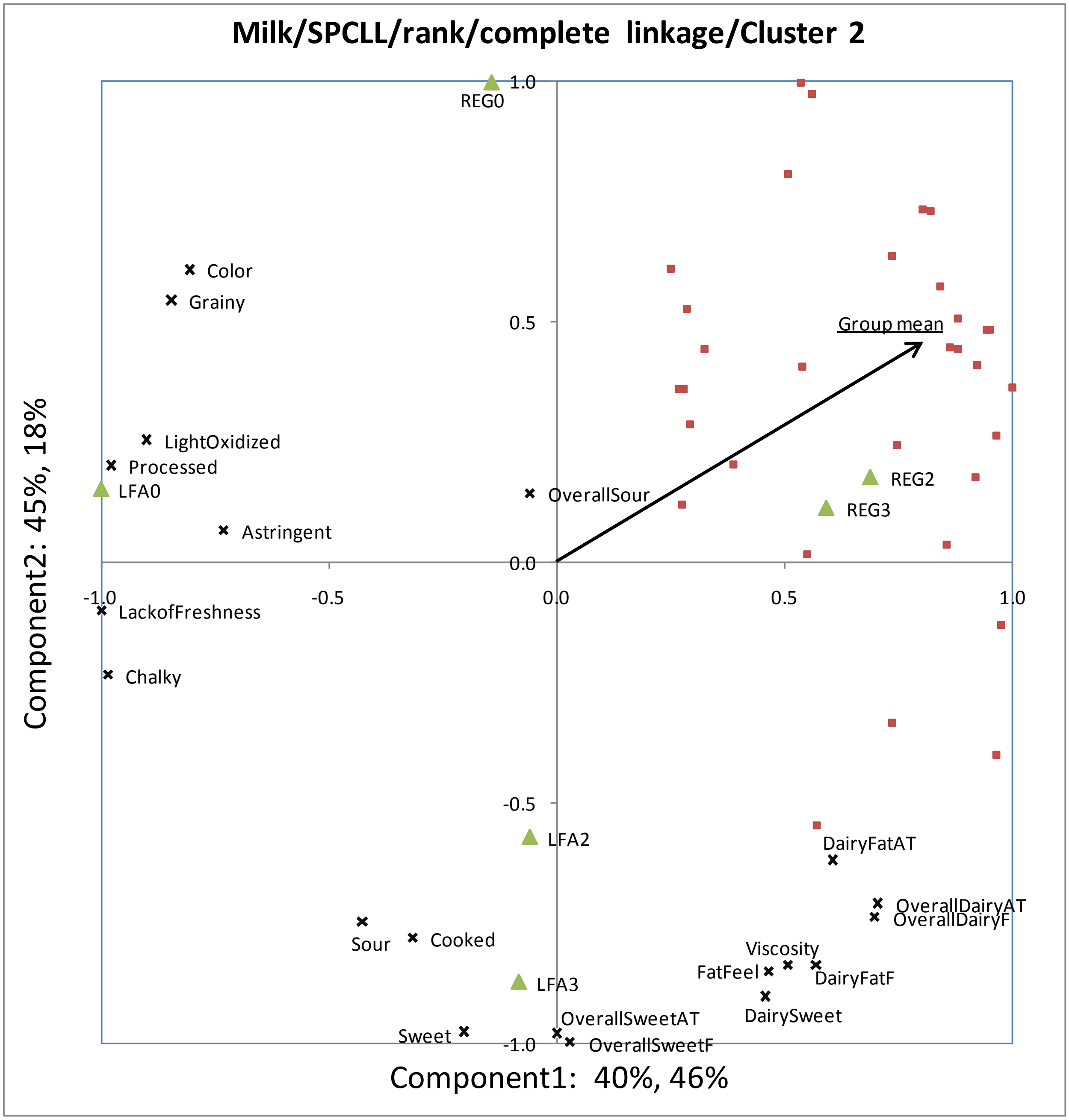

FIG. 4.8 EXAMPLE OF AN UNHELPFUL PLS2 MAP

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

TABLE4.3 NUMBER OF EXTERNAL PREFERENCE (PLS2) MAPS THAT PROVIDE HELPFUL/UNHELPFUL INTERPRETATIONS

Study	Score type/computer cluster	SPC		SPCLL		SPCLS		SMC		Total
		Helpful	Unhelpful	Helpful	Unhelpful	Helpful	Unhelpful	Helpful	Unhelpful	helpful maps
Milk	Hedonic/k-means	1	2	1	2	1	2	1+R	1	5
	Hedonic/Ward's	0	3	0	3	0	3	R	2	1
	Rank/complete linkage	1	2	1	2	2	1	1	2	5
	Rank/Ward's	0	3	0	3	0	3	R	2	1
	Total helpful maps	2	10	2	10	3	9	2	7	na
Fragrance	Hedonic/complete linkage	0	3	0	3	2	1	1	2	3
	Hedonic/MCQ	0	2	0	2	0	2	0	1+R	0
	Rank/complete linkage	0	3	0	3	1	1	0	3	1
	Rank/Ward's	0	3	0	3	0	3	1	R R	1
	Total helpful maps	0	11	0	11	3	8	2	6	na

SPC = computer clustering method (Approach 1)
SPCLL = computerized clustering and limited to loose manual cluster (Approach 4)
SPCLS = computer clustering and limited to strict manual cluster (Approach 3)
SMC = strict manual clustering method (Approach 2)
Helpful = number of maps that meet all three criteria explained in the materials and methods section
Unhelpful = number of maps that do not meet all three criteria explained in the materials and methods section
R = a repeat of SMC map and is not counted into the column's total number, but is included in the rows' total number
na = not applicable

This means that the PLS2 preference maps did not always represent accurate products and product characteristics that influence consumer liking. The PLS2 provides some mathematic connection between descriptive sensory data and consumer data (this is the weakness in other preference mapping techniques). It is expected that a map created from higher homogeneity of liking patterns should contribute better consumer liking and descriptive sensory data. However, the interpretation of the PLS2 maps did not yield much improvement of the relation between product liking and products' characteristics because it shows a low number of helpful maps even when homogeneity of product preference in the data is increased. Moreover, using the mean liking vector to identify the most liked products is arbitrary because, 1) the mean vector was calculated from liking scores of divergent consumers especially when clustering by SPC methods; and 2) the highest and lowest liked products were in the same direction as the mean liking vector. For example Fig 4.9 (Milk/SPCLL/hedonic/k-means/Cluster 1) shows that consumers in this cluster liked product LFA3 the most but it was impossible to identify a disliked product using the map. Although based on the most frequently disliked products in the original liking data, product REG2 and REG0 were shown. This illustrates that the mean vector could not represent this information but the original data did.

Another example is Fig 4.9 (Milk/SMC/hedonic/the most frequently liked product REG3 and disliked product REG2) because descriptive data are mapped first in the external preference mapping, two products (REG2 and REG3) exist in the lower-right quadrant together. These two products are always opposite to "lack of freshness, astringent and chalky" attributes because of their low intensities, but this cluster contains consumers who rated REG3 the most frequently liked product and REG2 the most frequently disliked product. This makes it impossible to create a mean vector that differentiates these two products; therefore, they are mapped close to each other.

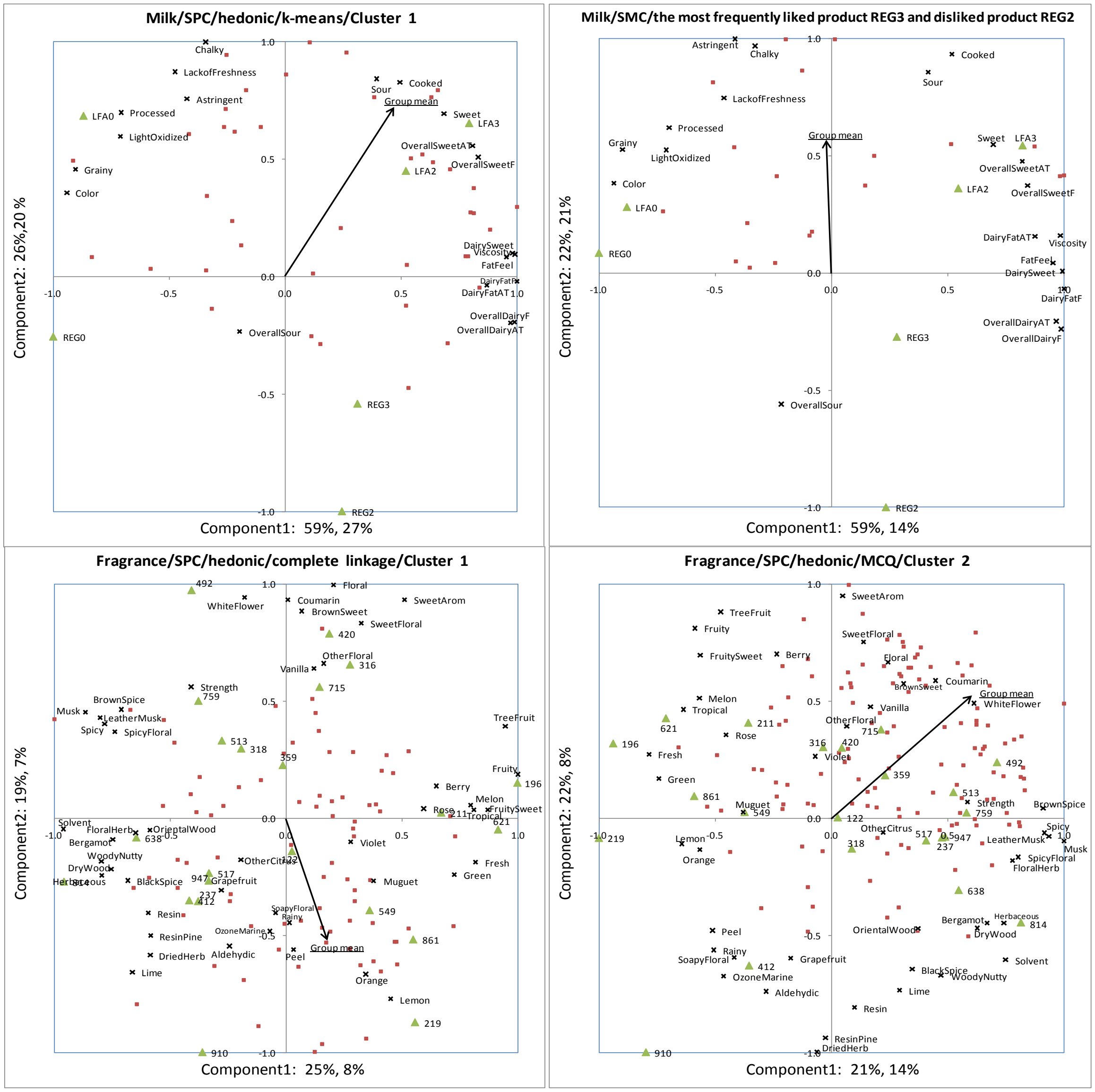

FIG. 4.9 EXAMPLES OF UNHELPFUL PLS2 MAPS CAUSING MISS-INTERPRETATION

[FatFeel = Fat feel, OverallDairyF = Overall dairy (flavor), DairyFatF = Dairy fat (flavor), DairySweet = Dairy sweet, LackofFreshness= Lack of freshness, LightOxidized = Light-oxidized, OverallSweetF = Overall sweet (flavor), OverallDairyAT = Overall dairy (aftertaste), DairyFatAT = Dairy fat (aftertaste), OverallSweetAT = Overall sweet (aftertaste), OverallSour = Overall sour]

Being unable to separate the most frequently liked and disliked product products also can be found in the fragrance study, e.g. Fig 4.9 (Fragrance/SPC/hedonic/complete linkage/cluster 1) where both product 621 and 196 were closed to each other because both products had high intensities in “strength, fruity, tropical, and tree fruit” attributes. Though these samples are not well separated in the maps, exploration of the original consumer data and descriptive sensory data helps in map explanation. Fig 4.9 (Fragrance/SPC/hedonic/MCQ/Cluster 2) also mapped product 517 closely to 318 because both had the same attributes in higher intensities than the other products. Therefore, interpretations and further analyses based information of a preference map configuration alone may not give target markets what is needed because the map could not show all relationships based on the linear regression form.

Conclusion

This study illustrates that using combinations of manual clustering and SPC produced more homogeneous clusters than any single method. Percent explained variances in consumers of SPCLS, the most homogenous cluster, yielded the highest percentage in each MDPREF and PLS2 maps for the milk and fragrance studies. Also SPCLS and SPCLL maps allocated consumers within narrower areas than the SMC and SPC maps. These smaller areas indicate that consumer map spaces were improved. However, the descriptive map spaces did not show much change in the descriptive map configuration or improvement in the percent explained variances of the descriptive attributes. Although consumer data are expected (PLS2 calculation) to be incorporated into the calculation of the descriptive map space; however, this study showed few differences among the descriptive configuration calculated for the same descriptive data and different consumer clusters that represented various homogenous liking patterns.

Using a liking mean vector did not necessarily help in identifying the most frequently liked/disliked products. Based on the three criteria for being a helpful map, the results neither showed a clear increase in the number of helpful maps across combinations of data types and SPC methods, nor with the SPCLS clusters. However, when interpreting an external preference map with product average liking scores, the most frequently liked/disliked products and high/low intensities of descriptive attributes help understand the maps better. This statement is true even for preference maps that were created based on more homogenous product liking such as those found in the manual clustering methods, which contain consumers who had the same highest and lowest liked products.

It is important to recognize that when identifying a sensory location or "map space" for a new prototype, positive and negative attributes are not based merely on a preference map itself. The original data and key findings from the descriptive study, from cluster liking mean scores, and the most/least liked products of each cluster must be reviewed along with the preference maps to assist in each map's interpretation.

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Appendices

Appendix A - SAS Template Used for Performing ANOVA on Original Consumer Liking Data

```
option nodate pageno = 1;
data step1;
input Consumer$  Code$ Liking ;
cards;

[DATA]

;run;

ods rtf;

proc glimmix data = step1;
title 'Overall Liking';
class consumer code;
model Liking = code/ddfm=satterth;
random consumer;
lsmeans code/pdiff lines;
run;

ods rtf close; quit;
```

Appendix B - SAS Template Used for Determining Number of Clusters in Consumer Studies

```
data one;
input Cons$  SAMPLE1 SAMPLE2 SAMPLE3  SAMPLE4  SAMPLE5 SAMPLE6;
datalines;

[DATA]

;

proc cluster data=one outtree=treew method=ward pseudo std  CCC ;
id Cons;
Var SAMPLE1--SAMPLE6;
run;
legend1 frame cframe=ligr
position=center value=(justify=center);
axis1 label=(angle=90 rotate = 0) minor=none order=(0 to 44 by 2);
axis2 minor=none order=( 1 to 28 by 1);

proc gplot;
plot _CCC_*_ncl_ /
frame cframe=ligr legend=legend1 Vaxis= axis3 haxis= axis2;
PLOT _PSF_*_NCL_ _PST2_*_NCL_ /OVERLAY
frame cframe=ligr legend=legend1 Vaxis= axis1 haxis= axis2;
run;
```

Appendix C - SAS Template used for Performing Statistical Package Cluster Analyses on Consumer Liking or Ranking Data

Hierarchical Clustering

```
data one;
input Cons $ SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5 SAMPLE6;
datalines;

[DATA]


;

proc cluster data=one outtree=treew method=MCQ ;

****The "method = MCQ  " were replaced by the following syntax for clustering methods
used in this research****;

**"method = MED" for median linkage clustering***;
**"method = SIN" for single linkage clustering***;
**"method = COM" for complete linkage clustering***;
**"method = WAR" for Ward's clustering***;
**"method = AVE" for average linkage clustering***;

id Cons;
Var SAMPLE1--SAMPLE6;
run;


proc tree data=treew nclusters=3 out= result1 sort;
id Cons; run;
```

```
Proc sort data=result1;by cluster;run;
proc sort data=result1;by Cons;run;
proc sort data=one;by Cons;run;

data merc;
merge result1 one;by Cons;run;

ods rtf;
proc print data=merc;run;
ods rtf close; quit
```

Partitional Clustering

```
data one;
input Cons $ SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5 SAMPLE6;
datalines;

[DATA]

;
proc fastclus data=one maxclusters=3 drift random=2342901 out=kmean
outseed=temp;
id Cons;
Var SAMPLE1--SAMPLE6;
run;
data kmean2; set kmean;
keep cons cluster;run;
proc sort data=kmean2;by Cons;run;
proc sort data=one;by Cons;run;

data merc;
```

```
merge kmean2 one;by Cons;run;

ods rtf;
proc print data=merc;run;
ods rtf close; quit
```

Density-based Clustering

```
data one;
input Cons $ SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5 SAMPLE6;
datalines;

[DATA]

;
****Nonparametric method code***;
Proc modeclus method=1 r= 1 2 3 4 5 6 out = treew;
var SAMPLE1--SAMPLE6;
run;
proc tree data=treew nclusters=3 out= result1 sort;
id Cons; run;
Proc sort data= result1;by cluster;run;

****Two-stage density linkage method code***;
proc cluster data=one outtree=trestage method=twostage k=3  ;
id Cons;
Var SAMPLE1--SAMPLE6;
run;
proc tree data= trestage nclusters=3 out= resstage sort;
id Cons; run;
Proc sort data= resstage;by cluster;run;
proc freq data= resstage;run;
```

```
proc sort data= resstage;by Cons;run;
proc sort data=one;by Cons;run;

data mergst;
merge resstage one;by Cons;run;

ods rtf;
proc print data=mergst;run;
ods rtf close; quit
```

Appendix D - SAS Template Used for Performing ANOVA on Each Consumer Cluster: Chapter 3

```
data step1;
Title 'individual cluster data';
input Cons $ CLUSTER SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5
SAMPLE6
;
cards;

[DATA]

;run;
proc sort;by Cons;run;
proc transpose  out = step2(rename= (cons=cons cluster=cluster _NAME_=code
col1=Liking));
by cons cluster;
run;
proc sort data =step2 out=step3;
by cluster cons;run;

title ' Kr /subject cons /tukey';
proc glimmix data = step3;
title 'Overall Liking of clusters by R';
class cons cluster code;
model Liking = cluster|code/ddfm=Kr;
random cons(cluster)/ subject = cons;
lsmeans cluster*code/adjust=tukey adjdfe=row;

ods output diffs=ppp lsmeans=mmm;
ods listing exclude diffs lsmeans;
run;
```

```
%include 'C:\Documents and Settings\...\pdmix800.sas';
%pdmix800 (ppp,mmm,alpha=.05, sort=yes);
run;
```

Appendix E - SAS Template Used for Manual Clustering on Consumer Data: Chapters 3 and 4

Strict Cluster and Strict-liking-only Cluster

```
data long3;
INPUT Consumer$  Code$liking
 ;
***hedonic consumer data***;
cards;

[DATA]

;run;
PROC SORT; BY consumer Code;run;
proc sort ; by consumer;run;
proc transpose  out=wide3 ;
   by consumer        ;
   id Code;
   var liking;
run;
proc print; run;
DATA TEMP2b;
 SET wide3;
 MAX =MAX( SAMPLE1,   SAMPLE2,   SAMPLE3,   SAMPLE4,   SAMPLE5,
          SAMPLE6);
 MIN =MIN( SAMPLE1,     SAMPLE2,   SAMPLE3,   SAMPLE4,   SAMPLE5,
          SAMPLE6);
  RUN;
proc print; run;
data temp2; set temp2b;
 if SAMPLE1=         SAMPLE2=   SAMPLE3=   SAMPLE4=   SAMPLE5=   SAMPLE6
```

```
 then delete;
 run;
 proc print; run;
  **----------------------------------------------------------------------**;
  ******manual clustering for consumers who most liked SAMPLE6 (strict-liking-only
cluster)****;
  data datamax;
 set TEMP2;
  if SAMPLE6 = max then pref = 'SAMPLE6'; if SAMPLE6 = max then output;
 run;
 data twomin;
 set datamax;
if SAMPLE1=min then disl='SAMPLE1'; if SAMPLE1=min then output;
if SAMPLE2=min then disl='SAMPLE2'; if SAMPLE2=min then output;
if SAMPLE3=min then disl='SAMPLE3'; if SAMPLE3=min then output;
if SAMPLE4=min then disl='SAMPLE4'; if SAMPLE4=min then output;
if SAMPLE5=min then disl='SAMPLE5'; if SAMPLE5=min then output;
if SAMPLE6=min then disl='SAMPLE6'; if SAMPLE6=min then output;
run;
proc print; run;
proc sort data=twomin ;by disl;run;
proc freq data=twomin;table disl; run; proc print; run;
   **----------------------------------------------------------------------**;
******manual clustering for consumers who most liked SAMPLE6 hated SAMPLE1 (strict
cluster)****;
data datamax2;
 set datamax;
 if SAMPLE1=min then disl='SAMPLE1';
 if SAMPLE1=min then output;
run;
```

Loose Cluster and Loose-liking-only Cluster

```
data long3;
 INPUT Consumer$        Code$        liking
 ;
***hedonic consumer data***;
cards;

[DATA]

;run;
PROC SORT; BY consumer Code;run;
proc sort ; by consumer;run;

proc transpose  out=wide3 ;
  by consumer        ;
  id Code;
  var liking;
run;
proc print; run;
DATA TEMP2b;
 SET wide3;
 MAX =MAX( SAMPLE1,   SAMPLE2,   SAMPLE3,   SAMPLE4,   SAMPLE5,
          SAMPLE6);
 MIN =MIN( SAMPLE1,     SAMPLE2,   SAMPLE3,   SAMPLE4,   SAMPLE5,
          SAMPLE6);
RUN;
proc print; run;
data temp2; set temp2b;
 if SAMPLE1=        SAMPLE2=   SAMPLE3=   SAMPLE4=   SAMPLE5=   SAMPLE6
 then delete;
 run;
```

```
proc print; run;
**------------------------------------------------------------------------**;
  ******manual clustering for consumers who most or second most liked SAMPLE6
(loose-ling-only cluster)****;
data temp2max;
 set TEMP2;
  if SAMPLE6=max then pref='SAMPLE6';
 if SAMPLE6= MAX-1 then pref=1;
 if SAMPLE6=max or SAMPLE6 = MAX-1 then output;
proc print; run;
data temp2min;
 set temp2max;
if SAMPLE1=min then disl='SAMPLE1'; if SAMPLE1=min then output;
if SAMPLE2=min then disl='SAMPLE2'; if SAMPLE2=min then output;
if SAMPLE3=min then disl='SAMPLE3'; if SAMPLE3=min then output;
if SAMPLE4=min then disl='SAMPLE4'; if SAMPLE4=min then output;
if SAMPLE5=min then disl='SAMPLE5'; if SAMPLE5=min then output;
if SAMPLE6=min then disl='SAMPLE6'; if SAMPLE6=min then output;
proc print; run;
proc sort data=temp2min; by pref disl;run;
proc freq data=temp2min;table disl; run; proc print; run;
  **---------------------------------------------------------------------**;
 ******manual clustering for consumers who most or second most liked SAMPLE6, and
most or second most liked SAMPLE1(loose cluster)****;
data temp2ia;
 set TEMP2max;
 if SAMPLE1=min then disl='SAMPLE1';
 if SAMPLE1= MIN+1 then disl=1;
 if SAMPLE1=min or SAMPLE1= MIN+1 then output;
run;proc print; run;
proc sort data = temp2ia;by Consumer;run;
```

Appendix F - SAS Template to Obtain Common Consumers between Manual Clustering and Statistical Package Clustering: Chapters 3 and 4

Example: SPCLS (Approach 3)

```
Title 'Cluster analysis of Milk';
data a;
input Cons FR3HL0$         ;
cards;

[DATA]
;
data g1;
input Cons mem1$ cluster SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5
SAMPLE6;
cards;

[DATA]

;run;
data g2;
input Cons mem2$  cluster SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5
SAMPLE6;
cards;

[DATA]

;run;
data g3;
input Cons mem3$  cluster SAMPLE1 SAMPLE2 SAMPLE3 SAMPLE4  SAMPLE5
SAMPLE6;
```

```
cards;

[DATA]

;run;
data z;
input Cons cons2$;
****dummy set to be able to match cons=FREG3;
cards;

[DATA]
;
data all ;
merge a g1 g2 g3  z ; by Cons ;
proc print;
run;

title ' Strict FR3HL0';
data all2s;set all;
if cons2 = FR3HL0 then output ;else delete;
 DATA all3s;set all2s;
        if mem1 = FR3HL0 then  output;
        if mem2= FR3HL0  then  output;
run;
```

Appendix G - MDPREF SAS Template: Chapters 2 and 4

```
data step1;
input Consumer$     Sample$ overall;
cards;

[DATA]

;
proc sort; by sample;run;
proc transpose data=step1 out=steptran prefix=C;
        by sample;
        id consumer;
        var overall;
run;
proc print data = steptran;
run;
/*
proc print; run;
proc transpose data=y1 out=steptran; id consumer;
proc print data=steptran; run;*/
ods rtf;
proc factor data=steptran scree score cov outstat=dstuff
rotate=none method=prin;
var C1-C115;
proc score data=steptran scores=dstuff out=dscore;
var C1-C115;
proc print data=dscore; run;
%plotit (data=dscore, plotvars=factor1 factor2, labelvar=_name_, vtoh=1.75);
run; quit;
ods rtf close;quit;
```

Appendix H - PCA SAS Template: Chapters 2 and 4

```
data meanyog;
input  Code $ MLiking A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17
A18 A19 A20;
cards;

[DATA]

;/*ods rtf;*/
proc sort;by code; run;
proc factor data=meanyog nfactors=2 outstat=yogstuff scree corr score rotate=none
method=prin  mineigen=0.01;
var  MLiking A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19
A20;
proc print; run;
proc score data=meanyog scores=yogstuff out=yogscore;
var  MLiking A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19
A20;
proc print data=yogscore;proc print;run;
%plotit (data=yogscore, plotvars =factor1 factor2, labelvar=code, vtoh=1.75);run;quit;
ods rtf close;quit;
```

Appendix I - Modified PREFMAP SAS Template[1]: Chapter 2

```
data meanyog;
input  Code $ A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19
A20;
cards;

[DATA]

;ods rtf ;
proc sort;by code; run;
proc factor data=meanyog nfactors=2 outstat=yogstuff scree cov score rotate=none
method=prin mineigen=0.01;
var  A1--A20;
proc print; run;
proc score data=meanyog score=yogstuff out=yogscore;
var  A1--A20;
proc means data=yogscore noprint; by code;
var factor1-factor2;
output out=means(drop=_TYPE_ _FREQ_)mean=factor1-factor2;
run;
data C;
input consumer$ code$ score;
cards;

[DATA]

;
proc sort data=c; by code;run;
```

[1] From Dr. Hildegarde Heymann's class notes

```
Proc freq data=c;run; proc print data=yogurtc; run;
proc sort data=means;
by code;
proc print;
proc sort data=c;
by code;
proc print;
data f;
merge means yogurtc; by code;
F1SQ=FACTOR1**2; F2SQ=FACTOR2**2;
%AUTOFIT (f, consumer, score, FACTOR1 FACTOR2, F1SQ F2SQ);
RUN;
data descon (keep = code consumer factor1-factor2);
set yogscore all;
proc print data=descon;
run;
ods rtf close;quit
```

Appendix J - CVA SAS Template[1]: Chapter 2

```
Data cva;
input judge$ prod$  Rep$  A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15
A17 A18 A19 A20;
datalines;
[DATA]

;run;/*ods rtf;*/
proc sort; by prod;run;
proc discrim data= cva anova manova canonical outstat=yogstuff;
class prod;
var A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19 A20;
run;

proc score data=cva score=yogstuff out=yogscore;
var  A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19 A20;
data yog2;set yogstuff;
if _TYPE_= 'SCORE';
run;
proc transpose data=yog2
          out=yog2tran;
run;

data yog3;set yogstuff;
if _TYPE_= 'CANMEAN' ;
drop A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19 A20;
run;
proc transpose data=yog3
```

[1] Modified from Dr. Hildegarde Heymann's class notes

```
        out=yog3tran;by prod;
run;
data means;set yog3tran;drop _NAME_ _TYPE_;run;
/*proc print data=means;run;*/

data C;
input consumer$ prod$ score;
cards;

[DATA]
;
proc sort data=c; by prod;run;
Proc freq data=c;run; proc print data=c; run;
proc sort data=means; by prod;run;
proc sort data=c;
by prod;run;

data f;
merge means c; by prod;
C1SQ=CAN1**2; C2SQ=CAN2**2;
%AUTOFIT (f, consumer, score, CAN1 CAN2, C1SQ C2SQ);
RUN;
data descon (keep = prod consumer CAN1-CAN2);
set means all;
proc print data=descon;
run;
```

Appendix K - PLS (in Chapter 2) and PLS2 (in Chapters 2 and 4) SAS Templates[1]

```
%macro res_plot(ds);

data _NULL_; set &ds;
  call symput('max_n',n);
run;

%do i=1 %to &num_y;

  axis1 label=(angle=270 rotate=90 "Residual")
        major=(number=5) minor=none;

  axis2 label=("Prediction for Response &i") minor=none;

  data res_anno;     *** Annotation Data Set for Plot ***;
    length text $ %length(&max_n);
    retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
    set &ds;
    text=%str(n);  x=&predname&i;  y=y&resname&i;
  run;

  proc gplot data=&ds;
    plot y&resname&i*&predname&i/anno=res_anno vaxis=axis1
                             haxis=axis2 vref=0 lvref=2 frame;
    symbol1 v=none i=none;
  run;
```

[1] ELSHEIMER, B. and TOBIAS R. 2010. Example using SAS PLS procedure. http://support.sas.com/rnd/app/papers/plsex.pdf (accessed March 10, 2010)

```
%end;

%mend;

%macro nor_plot(ds);

data ds; set &ds;
run;

data _NULL_; set &ds;
  call symput('max_n',n);
run;


%do i=1 %to &num_y;
  data ds; set ds;
    if y&resname&i=. then delete;
  run;
%end;

data _NULL_; set ds;
  call symput('numobs',_N_);
run;

%do i=1 %to &num_y;

  proc sort data=ds; by y&resname&i;

  /*********************************************************
  /  Calculate the expected values under normality for each  /
  /  residual.                                               /
```

```
  ***********************************************************/

  data resid&i; set ds(keep=n y&resname&i);
   v=(_n_ - 0.375)/(&numobs+0.25);
   z=probit(v);
  run;

  axis1 label=(angle=270 rotate=90 "Y&i Residual")
       major=(number=5) minor=none;

  axis2 label=('Normal Quantile') minor=none;

  data nor_anno;            *** Annotation Data Set for Plot ***;
   length text $ %length(&max_n);
   retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
   set resid&i;
   text=%str(n); x=z; y=y&resname&i;
  run;

  proc gplot data=resid&i;
   plot y&resname&i*z/anno=nor_anno vaxis=axis1 haxis=axis2
                  frame;
   symbol1 v=none i=none;
  run;

%end;

%mend;

%macro plot_scr(ds,
              max_lv=&lv);
```

```
data dsout; set &ds;      *** Uses nonmissing observations ***;
  if n ^= .;
run;

data _NULL_; set &ds;
  call symput('max_n',n);
run;


%do i=1 %to &max_lv;

  data pltanno;          *** Annotation Data Set for Plot ***;
    length text $ %length(&max_n);
    retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
    set dsout;
    text=%str(n); x=&xscrname&i; y=&yscrname&i;
  run;

  axis1 label=(angle=270 rotate=90 "Y score &i")
        major=(number=5) minor=none;

  axis2 label=("X-score &i") minor=none;

  proc gplot data=dsout;
    plot &yscrname&i*&xscrname&i/anno=pltanno vaxis=axis1
                             haxis=axis2 frame;
    symbol1 v=none i=none;
  run;

%end;
```

```
%mend plot_scr;

%macro plotxscr(ds,
               max_lv=&lv);

data dsout; set &ds;
  if n ^= .;              *** Uses nonmissing observations ***;
run;

data _NULL_; set &ds;
  call symput('max_n',n);
run;

%do i=1 %to %eval(&max_lv-1);

  %let j=%eval(&i+1);

  data pltanno;           *** Annotation Data Set for Plot ***;
    length text $ %length(&max_n);
    retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
    set dsout;
    text=%str(n); x=&xscrname&i; y=&xscrname&j;
  run;

  axis1 label=(angle=270 rotate=90 "X score &j")
       major=(number=5) minor=none;

  axis2 label=("X-score &i") minor=none;

  proc gplot data=dsout;
    plot &xscrname&j*&xscrname&i/anno=pltanno vaxis=axis1
```

```
                                haxis=axis2 frame;
    symbol1 v=none i=none;
  run;

%end;

%mend plotxscr;

%macro get_wts(dsoutmod,
               dsxwts=xwts);

data &dsxwts; set &dsoutmod(keep=_TYPE_ _LV_ &xvars);
  if _TYPE_='WB' then output;

proc transpose data=&dsxwts out=&dsxwts; run;

data &dsxwts; set &dsxwts;
  if _NAME_='_LV_' then delete;
  n=_n_-1;
run;

%do i=1 %to &lv;

  data &dsxwts; set &dsxwts;
    rename col&i=w&i;
  run;

%end;

%mend;
```

```
%macro plot_wt(ds,
               max_lv=&lv);

 /*********************************************************
 /  Determine the largest label to be put on plot          /
 *********************************************************/

%let name_len=1;

data _NULL_; set &ds;
  call symput('num_x',_N_);
run;

%do i=1 %to &num_x;
  %let temp=%scan(&xvars,&i,%str( ));
  %if %length(&temp)>&name_len %then %do;
    %let name_len=%length(&temp);
  %end;
%end;

 /*********************************************************
 /  Plot X-weights for each PLS component                  /
 *********************************************************/

%do i=1 %to %eval(&max_lv-1);

  %let j=%eval(&i+1);

  data wt_anno;             *** Annotation Data Set for Plot ***;
    length text $ &name_len;
    retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
```

```
    set &ds;
    text=%str(_name_); x=w&i; y=w&j;
  run;

  axis1 label=(angle=270 rotate=90 "X weight &j")
        major=(number=5) minor=none;

  axis2 label=("X-weight &i") minor=none;

  proc gplot data=&ds;
    plot w&j*w&i/anno=wt_anno vaxis=axis1 haxis=axis2 frame;
    symbol1 v=none i=none;
  run;

%end;

%mend;

%macro pltwtfrq(ds,
            plotyvar=W,
            plotxvar=f,
            max_lv=&lv,
            label=Weight);

axis1 label=(angle=270 rotate=90 "&label")
      major=(number=5) minor=none;
axis2 label=("Frequency") minor=none;

%let plotvars=%str( );

%do i=1 %to &max_lv;
```

```
  %let plotvars=%str(&plotvars &plotyvar&i);
%end;

proc gplot data=&ds;
  plot (&plotvars)*&plotxvar/overlay legend vaxis=axis1
                          haxis=axis2 vref=0 lvref=2 frame;
  symbol1 v=none i=spline;
run;

%mend;

%macro getxload(dsoutmod,
               dsxload=xloads);

data &dsxload; set &dsoutmod(keep=_TYPE_ &xvars);
  if _TYPE_='PQ' then output;

proc transpose data=&dsxload out=&dsxload; run;

data &dsxload; set &dsxload;
  n=_N_;
run;

%do i=1 %to &lv;

  data &dsxload; set &dsxload;
    rename col&i=p&i;
  run;

%end;
```

```
%mend;

%macro pltxload(ds,
        max_lv=&lv);

/********************************************************
/ Determine the largest label to be put on plot        /
********************************************************/

%let name_len=1;

data _NULL_; set &ds;
 call symput('num_x',_N_);
run;

%do i=1 %to &num_x;
 %let temp=%scan(&xvars,&i,%str( ));
 %if %length(&temp)>&name_len %then %do;
  %let name_len=%length(&temp);
 %end;
%end;

/********************************************************
/ Plot X-loadings for each PLS component                /
********************************************************/

%do i=1 %to %eval(&max_lv - 1);

 %let j=%eval(&i+1);

 data pltanno;        *** Annotation Data Set for Plot ***;
```

```
   length text $ &name_len;
   retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
   set &ds;
   text=%str(_name_); x=p&i; y=p&j;
  run;

  axis1 label=(angle=270 rotate=90 "X loading &j")
      major=(number=5) minor=none;

  axis2 label=("X-loading &i") minor=none;

  proc gplot data=&ds;
   plot p&j*p&i/anno=pltanno vaxis=axis1 haxis=axis2 frame;
   symbol1 v=none i=none;
  run;

%end;

%mend;

%macro getyload(dsoutmod,
              dsyload=yloads);

 data &dsyload; set &dsoutmod(keep=_TYPE_ _LV_ &yvars);
  if _TYPE_='PQ' then output;

proc transpose data=&dsyload out=&dsyload; run;

data &dsyload; set &dsyload;
  if _NAME_='_LV_' then delete;
run;
```

```
%do i = 1 %to &lv;

  data &dsyload; set &dsyload;
    rename col&i=q&i;
  run;

%end;

%mend;

%macro plt_y_lv(dsoutmod);

data dsyload; set &dsoutmod(keep=_TYPE_ _LV_ &yvars);
  if _TYPE_='PQ' then output;

goptions reset=symbol;

axis1 label=(angle=270 rotate=90 'Y loading')
      major=(number=5) minor=none;
axis2 label=('PLS Component') order=(1 to &lv by 1) minor=none;

proc gplot data=dsyload;
  plot (&yvars)*_LV_/overlay legend vaxis=axis1 haxis=axis2
                  vref=0 lvref=2 frame;
run;

%mend;

%macro pltyload(ds,
               max_lv=&lv);
```

```
/***********************************************************
/  Determine the largest label to be put on plot            /
***********************************************************/

data _NULL_; set &ds;
 call symput('num_y',_N_);
run;

%let name_len=1;

%do i=1 %to &num_y;
 %let temp=%scan(&yvars,&i,%str( ));
 %if %length(&temp)>&name_len %then %do;
   %let name_len=%length(&temp);
 %end;
%end;

/***********************************************************
/  Plot Y-loadings for each PLS component                  /
***********************************************************/

%do i=1 %to %eval(&max_lv+1);

 %let j=%eval(&i+1);

 data pltanno;            *** Annotation Data Set for Plot ***;
   length text $ &name_len;
   retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
   set &ds;
```

```
    text=%str(_NAME_); x=q&i; y=q&j;
  run;

  axis1 label=(angle=270 rotate=90 "Y loading &j")
        major=(number=5) minor=none;

  axis2 label=("Y-loading &i") minor=none;

  proc gplot data=&ds;
    plot q&j*q&i/anno=pltanno vaxis=axis1 haxis=axis2;
    symbol1 v=none i=none;
  run;

%end;

%mend;

%macro pltxywts(dsxwts,
               dsyloads,
               norm=1,
               max_lv=&lv);

data _NULL_; set &dsxwts;
  call symput('num_x',_N_);
run;

data _NULL_; set &dsyloads;
  call symput('num_y',_N_);
run;

%let name_len=1;
```

```
%do i=1 %to &num_x;
 %let temp=%scan(&xvars,&i,%str( ));
 %if %length(&temp)>&name_len %then %do;
  %let name_len=%length(&temp);
 %end;
%end;

%let nameleny=1;

%do i=1 %to &num_y;
 %let temp=%scan(&yvars,&i,%str( ));
 %if %length(&temp)>&nameleny %then %do;
  %let nameleny=%length(&temp);
 %end;
%end;

%if &name_len < &nameleny %then %let name_len = &nameleny;

/*********************************************************
/  Normalize weights if desired                          /
*********************************************************/

%if %eval(&norm) %then %do;

proc iml;
 use &dsxwts;
 read all var ("w1":"w&max_lv") into W;
 use &dsyloads;
 read all var ("q1":"q&max_lv") into Q;
 W=W#sqrt(1/W[##,]);  *** Normalize X-weights ***;
```

```
  Q=Q#sqrt(1/Q[##,]);  *** Normalize Y-loadings ***;
  w_col=("WQ1":"WQ&max_lv");
  _NAME_={&xvars};
  create dsxwts from W[colname=w_col rowname=_NAME_];
  append from W[rowname=_NAME_];
  q_col=("WQ1":"WQ&max_lv");
  _NAME_={&yvars};
  create dsyloads from Q[colname=q_col rowname=_NAME_];
  append from Q[rowname=_NAME_];
quit;

%end;

%else %do;

data dsxwts; set &dsxwts;

data dsyloads; set &dsyloads;

%end;


 /************************************************************
 /  Plot X-weights and Y-loadings for each PLS component    /
 ************************************************************/

%if &name_len>&nameleny %then %do;
  data ds; set dsxwts dsyloads;
%end;
%else %do;
  data ds; set dsyloads dsxwts;
```

```
%end;

%do i=1 %to %eval(&max_lv-1);

 %let j=%eval(&i+1);

 data wt_anno;            *** Annotation Data Set for Plot ***;
  length text $ &name_len;
  retain function 'label' position '5' hsys '3' xsys '2' ysys '2' ;
  set ds;
  text=%str(_name_); x=wq&i; y=wq&j;
 run;

 axis1 label=(angle=270 rotate=90 "Component &j Weight")
     major=(number=5) minor=none;

 axis2 label=("Component &i Weight") minor=none;

 proc gplot data=ds;
  plot wq&j*wq&i/anno=wt_anno vaxis=axis1 haxis=axis2 frame
                 vref=0 href=0;
  symbol1 v=none i=none;
 run;

%end;

%mend;

%macro get_bpls(dsoutmod,
        dsout=bpls);
```

```
data est_wb; set &dsoutmod;  if _TYPE_='WB' then output; run;
data est_pq; set &dsoutmod;  if _TYPE_='PQ' then output; run;

proc iml;
  use est_wb;
  read all var {&xvars} into w_prime;
  read all var {_Y_} into b;
  use est_pq;
  read all var {&xvars} into p_prime;
  read all var {&yvars} into q_prime;
  W=w_prime`;
  P=p_prime`;
  Q=q_prime`;
  B_PLS = W*inv(P`*W)*diag(b)*Q`;
  b_col=('B1':"B&num_y");
  x_var={&xvars};
  create &dsout from B_PLS[colname=b_col rowname=x_var];
  append from B_PLS[rowname=x_var];
quit;

%mend;

%macro plt_bpls(ds);

data &ds; set &ds;
  f=_n_;
run;

%let plotvars=%str( );

%do i=1 %to &num_y;
```

```
  %let plotvars=%str(&plotvars b&i);
%end;

axis1 label=(angle=270 rotate=90 'Coefficient')
     major=(number=5) minor=none;
axis2 label=('Frequency') minor=none;

proc gplot data=&ds;
  plot (&plotvars)*f / overlay legend vaxis=axis1 haxis=axis2
                    vref=0 lvref=2 frame;
  symbol1 v=none i=spline;
run;

%mend;

%macro get_vip(dsoutmod,
              dsvip=vip_data);

data dsxwts; set &dsoutmod(keep=_TYPE_ _LV_ &xvars);
  if _TYPE_='WB' then output;

data y_rsq; set &dsoutmod(keep=_LV_ _TYPE_ &yvars _Y_);
  if _TYPE_='V' then output;
  drop _TYPE_;
run;

data y_rsq; merge y_rsq dsxwts; by _LV_;
  if _LV_=0 then delete;
run;

proc iml;
```

```
  use y_rsq;
  read all var {_Y_} into rsq_y;
  read all var {&xvars} into w_prime;
  A=nrow(rsq_y);
  K=ncol(w_prime);
  W=w_prime`;
  Wnorm=W#(1/sqrt(W[##,]));
  if A > 1 then do;
    part_rsq=rsq_y-(0//rsq_y[1:(A-1),]);
    tot_rsq=rsq_y[A,];
    vip_sq=((Wnorm##2)*part_rsq)#(K/tot_rsq);
    VIP=sqrt(vip_sq);
  end;
  else VIP=Wnorm#sqrt(K);
  x_var={&xvars};
  create &dsvip from VIP[colname='VIP' rowname=x_var];
  append from VIP[rowname=x_var];
quit;

%mend;

%macro plot_vip(ds);




data &ds; set &ds;
  f=_N_;
run;

axis1 label=(angle=270 rotate=90 'VIP')
      major=(number=10) minor=none;
```

```
axis2 label=('Frequency') minor=none;

proc gplot data=&ds;
  plot vip*f / overlay vaxis=axis1 haxis=axis2 vref=0.8 lvref=2
              frame;
  symbol1 v=none i=join;
run;

%mend;


%macro get_dmod(dsoutput,
               dsdmod=dmod,
               qresname=qres,
               id=n);
data trn_out; set &dsoutput;
  if y&qresname ^= . then output;
run;

proc means data=trn_out noprint;
  var xqres;
  output out=outmeans n=n mean=xqres_mn;
run;

data _NULL_; set outmeans;
  call symput('num_trn',n);
  call symput('xqres_mn', xqres_mn);
run;

proc iml;
  use &dsoutput;
```

```
  read all var {x&qresname} into xqres;
  read all var {y&qresname} into yqres;
  read all var{&id} into id;
  dmodx=sqrt(xqres/&xqres_mn);

  do i=1 to nrow(xqres);
    if yqres[i]=. then
       dmodx[i]=dmodx[i]/sqrt(&num_trn/(&num_trn-&lv-1));
  end;

  dmody=sqrt(yqres*(&num_trn/(&num_trn-&lv-1)));
  dmodboth=id||dmodx||dmody;
  col={&ID DMODX DMODY};
  create &dsdmod from dmodboth[colname=col];
  append from dmodboth;
quit;

%mend;

%macro cont_scr(est,
                out,
                dsout,
                obsnum,
                idvar=n,
                a=1);
data est; set &est;
  if (_TYPE_='WB' or _TYPE_='PQ') then output;
run;

data out; set &out;
  if &idvar=&obsnum then output;
```

```
run;

proc iml;
  use est;
  read all var {&xvars} into WP;
  W=WP[1:&lv,];
  P=WP[(&lv+1):(2*&lv),];
  Wstar=W`*inv(P*W`);
  use &out;
  read all var {&xvars} into X;
  use out;
  read all var {&xvars} into x_i;
  contrib=(Wstar[,&a])` # (x_i - X[:,]);
  quantity=('contrib');
  xvar={&xvars};
  create &dsout from contrib[rowname=quantity colname=xvar];
  append from contrib[rowname=quantity];
quit;

proc transpose data=&dsout out=&dsout; run;

data &dsout; set &dsout;
  rename col1=contrib;
run;

axis1 label=(angle=270 rotate=90 'Contribution');

axis2 label=('X-variable');

proc gplot data=&dsout;
  plot contrib * _NAME_ / haxis=axis2 vaxis=axis1;
```

```
  symbol1 i=needles v=dot;
run;
quit;

%mend;

%macro cont2scr(est,
                out,
                dsout,
                obsnum,
                idvar=n,
                a1=1,
                a2=2);
data est; set &est;
  if (_TYPE_='WB' or _TYPE_='PQ') then output;
run;

data out; set &out;
  if &idvar=&obsnum then output;
run;

proc iml;
  use est;
  read all var {&xvars} into WP;
  W=WP[1:&lv,];
  P=WP[(&lv+1):(2*&lv),];
  Wstar=W`*inv(P*W`);
  use &out;
  read all var {&xscrname&a1 &xscrname&a2} into T;
  read all var {&xvars} into X;
  use out;
```

```
  read all var {&xscrname&a1 &xscrname&a2} into t_i;
  read all var {&xvars} into x_i;
  delta_t1=t_i[,1]-T[:,1];
  delta_t2=t_i[,2]-T[:,2];
  sd_t1=sqrt((T[##,1]-nrow(T)*T[:,1]**2)/(nrow(T)-1));
  sd_t2=sqrt((T[##,2]-nrow(T)*T[:,2]**2)/(nrow(T)-1));
  w1star=Wstar[,&a1];
  w2star=Wstar[,&a2];
  v_sq=(delta_t1/sd_t1)**2*(w1star)`##2+
      (delta_t2/sd_t2)**2*(w2star)`##2;
  v=sqrt(v_sq);
  delta_x=x_i-X[:,];
  contrib=(v#delta_x);
  quantity=('contrib');
  xvar={&xvars};
  create &dsout from contrib[rowname=quantity colname=xvar];
  append from contrib[rowname=quantity];
quit;

proc transpose data=&dsout out=&dsout; run;

data &dsout; set &dsout;
  rename col1=contrib;
run;

axis1 label=(angle=270 rotate=90 'Contribution');

axis2 label=('X-variable');

proc gplot data=&dsout;
  plot contrib * _NAME_ / haxis=axis2 vaxis=axis1;
```

```
  symbol1 i=needles v=dot;
run;
quit;

%mend;
data da;
input subject$ product$     Rep$  A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14
A15 A17 A18 A19 A20;
cards;

[DATA]

;

;
proc sort data=da out=sorted;
by product subject;
proc means data=sorted mean maxdec=5 print;
by product;
var  A1 A2 A3 A4 A5 A6 A7 A8 A9 A10 A11 A12 A13 A14 A15 A17 A18 A19 A20;
output out=meand mean= MEANA1 MEANA2 MEANA3 MEANA4 MEANA5 MEANA6
MEANA7 MEANA8 MEANA9 MEANA10 MEANA11 MEANA12 MEANA13 MEANA14
MEANA15 MEANA17 MEANA18 MEANA19 MEANA20;
proc print;
run;

****************************** SAS code for PLS1 *************************;
data consum;
input cons $ product$   like;
cards;
```

```
[DATA]

;
proc sort data=consum out=sortc;
by product;
proc means data=sortc mean maxdec=5 noprint;
by product; var like;
output out=meanc mean=mlike;
proc print;
run;
data one;
merge meand meanc; by product;
proc sort; by product;
proc print;
run;
%global xvars yvars predname resname xscrname yscrname num_x num_y lv;
%let xvars = MEANA1 MEANA2 MEANA3 MEANA4 MEANA5 MEANA6 MEANA7
MEANA8 MEANA9 MEANA10 MEANA11 MEANA12 MEANA13 MEANA14 MEANA15
MEANA17 MEANA18 MEANA19 MEANA20;
%let yvars = mlike;
%let ypred = yhat1;
%let yres = yres1;
%let predname = yhat;
%let resname = res;
%let xscrname = xscr;
%let yscrname = yscr;
%let num_y = 1;
%let num_x = 19;

proc pls data = one method = pls  outmodel =est1 lv = 2;
model &yvars = &xvars;
```

```
output out = outpls predicted = yhat1 stdx = stdx stdy = stdy xscore = xscr
yscore = yscr xresidual = xres1-xres19 yresidual = yres1 h = h t2 = t2 press = press
xqres=xqres yqres=yqres;
proc print;
run;
data outpls; set outpls; n=_N_; run;
data one; set one; n=_N_;run;
data predict; merge outpls one; by n;run;
%let lv=2;
%plot_scr (outpls);
%plotxscr(outpls, max_lv=2);
%get_wts(est1,dsxwts=xwts);
%plot_wt(xwts, max_lv=2);
 %getxload(est1,dsxload=xloads);
%pltxload(xloads, max_lv=2);
%res_plot(outpls);
%nor_plot(outpls);
%get_bpls(est1,dsout=bpls);
%get_vip(est1,dsvip=vip_data);

data eval;
merge bpls vip_data; run;
proc print data=eval; run;

****************************** SAS code for PLS2 *************************;
data meantpa;
input prod$ C1 C2  C3   C4   C5   C6   C7   C8   C9   C10  C11  C12
        C13  C14  C15  C16  C17  C18  C19  C20  C21  C22  C23  C24
        C25  C26  C27  C28  C29  C30  C31  C32  C33  C34  C35  C36
        C37  C38  C39  C40  C41  C42  C43  C44  C45  C46  C47  C48
        C49  C50  C51  C52  C53  C54  C55  C56  C57  C58  C59  C60
```

```
        C61  C62  C63  C64  C65  C66  C67  C68  C69  C70  C71  C72
        C73  C74  C75  C76  C77  C78  C79  C80  C81  C82  C83  C84
        C85  C86  C87  C88  C89  C90  C91  C92  C93  C94  C95  C96
        C97  C98  C99  C100 C101 C102 C103 C104 C105 C106 C107 C108
        C109 C110 C111 C112 C113 C114 C115;
cards;

[DATA]


;
proc sort data=meantpa ;
by prod;

data sentpa;
merge meansen meantpa; by prod;
proc sort; by prod;
proc corr  data= sentpa out=correlate pearsob;
var MEANA1 MEANA2 MEANA3 MEANA4 MEANA5 MEANA6 MEANA7 MEANA8
MEANA9 MEANA10 MEANA11 MEANA12 MEANA13 MEANA14 MEANA15 MEANA17
MEANA18 MEANA19 MEANA20 C1 C2 C3    C4   C5   C6   C7   C8   C9
        C10  C11  C12  C13  C14  C15  C16  C17  C18  C19  C20  C21
        C22  C23  C24  C25  C26  C27  C28  C29  C30  C31  C32  C33
        C34  C35  C36  C37  C38  C39  C40  C41  C42  C43  C44  C45
        C46  C47  C48  C49  C50  C51  C52  C53  C54  C55  C56  C57
        C58  C59  C60  C61  C62  C63  C64  C65  C66  C67  C68  C69
        C70  C71  C72  C73  C74  C75  C76  C77  C78  C79  C80  C81
        C82  C83  C84  C85  C86  C87  C88  C89  C90  C91  C92  C93
        C94  C95  C96  C97  C98  C99  C100 C101 C102 C103 C104 C105
        C106 C107 C108 C109 C110 C111 C112 C113 C114 C115
;run;
proc print;
```

```
run;
%global xvars yvars predname resname xscrname yscrname num_x num_y lv;
%let xvars = MEANA1 MEANA2 MEANA3 MEANA4 MEANA5 MEANA6 MEANA7
MEANA8 MEANA9 MEANA10 MEANA11 MEANA12 MEANA13 MEANA14 MEANA15
MEANA17 MEANA18 MEANA19 MEANA20;
%let yvars = C1 C2 C3   C4   C5   C6   C7   C8   C9   C10  C11  C12
        C13  C14  C15  C16  C17  C18  C19  C20  C21  C22  C23  C24
        C25  C26  C27  C28  C29  C30  C31  C32  C33  C34  C35  C36
        C37  C38  C39  C40  C41  C42  C43  C44  C45  C46  C47  C48
        C49  C50  C51  C52  C53  C54  C55  C56  C57  C58  C59  C60
        C61  C62  C63  C64  C65  C66  C67  C68  C69  C70  C71  C72
        C73  C74  C75  C76  C77  C78  C79  C80  C81  C82  C83  C84
        C85  C86  C87  C88  C89  C90  C91  C92  C93  C94  C95  C96
        C97  C98  C99  C100 C101 C102 C103 C104 C105 C106 C107 C108
        C109 C110 C111 C112 C113 C114 C115;
%let ypred = yhat1-yhat115;
%let yres = yres1-yres115;
%let predname = yhat;
%let resname = res;
%let xscrname = xscr;
%let yscrname = yscr;
%let num_y = 115;
%let num_x = 19;

proc pls data = sentpa method = pls outmodel =est1 lv = 2;
model &yvars = &xvars;
output out = outpls predicted = yhat1-yhat115 stdx = stdx stdy = stdy xscore = xscr
yscore = yscr xresidual = xres1-xres19 yresidual = yres1-yres115 h = h t2 = t2 press =
press
xqres=xqres yqres=yqres;
proc print;
```

```
run;
data outpls; set outpls; n=_N_; run;
data sentpa; set sentpa; n=_N_;run;
data predict; merge outpls sentpa; by n;run;
%let lv=2;
%plot_scr(outpls, max_lv=2);
%plotxscr(outpls, max_lv=2);
%get_wts(est1,dsxwts=xwts);
%plot_wt(xwts, max_lv=2);
%getxload(est1,dsxload=xloads);
%pltxload(xloads, max_lv=2);
%res_plot(outpls);
%nor_plot(outpls);
%get_bpls(est1,dsout=bpls);
%get_vip(est1,dsvip=vip_data);

data eval;
merge bpls vip_data; run;
proc print data=eval; run;
```