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Perceptual maps of photographs of carbonated beverages created by traditional and free-choice profiling

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Abstract

Perceptual maps of how consumers view a set of products are often constructed by profiling methods. One of the most common profiling techniques used is attribute rating analysis (ARA) in which consumers evaluate products on a prespecified set of attributes. Free-choice profiling (FCP) allows consumers to describe and evaluate products in their own terminology. The objective of this study was to compare the perceptual maps created from ARA and FCP. Forty-two persons evaluated photographs of twelve carbonated beverage brands using 13 specified attributes (ARA). Forty-four different persons, using the same product set, made evaluations based on their own criteria (FCP). The resulting perceptual maps were similar and dimensions from the two maps were significantly correlated. Large group variance in the Procrustes analysis further confirmed similarity of the perceptual maps. However, for these data the consumer FCP elicited more explicit attributes to describe the soda brands than the ARA.

1. Introduction

Perceptual mapping is a popular technique used to understand how consumers differentiate objects, such as brands in a product category (Moore & Pessimier, 1993; Pessimier, 1975). There are a number of ways in which this map can be derived, for example profiling techniques, the repertory grid method, free-choice profiling etc. In this paper we will compare the traditional profiling and a structured free-choice profiling techniques. In the traditional profiling method consumers evaluate products based on a prespecified set of attributes (Steenkamp, Van Trijp, & Ten Berge, 1994). This consumer method is considered a profiling technique. It is different from descriptive analysis, an analytical sensory technique, in which panelists develop a consensus vocabulary to evaluate the sensory attributes of products (Heymann, Holt, & Cliff, 1993), in that the consumers are given a list of attributes with no discussion of these. Traditionally, for either method, the information can be reduced to a two or three-dimensional space using principal component analysis (PCA).

Principal component analysis, a multi-variate technique, is used to transform the original evaluations into new uncorrelated dimensions. The dimensions are specified by obtaining a linear combination of the attribute evaluations that maximizes the differences (variance) among brands (objects). The resulting dimensions are believed to represent the basic psychological factors (dimensions) in consumers' perceptions (Urban, Hauser, & Oholakia, 1987).

The dimensions of the resulting perceptual map may initially not be interpretable. In some cases, especially with designed experiments, it is possible to use prior knowledge of the products to interpret the space. However, to understand these dimensions further, the relationship of the various attributes to the smaller number of more general dimensions is investigated. Attributes that load heavily on a particular dimension are used to interpret the dimensions (Urban et al., 1987). Products (objects) may be plotted into the space as points. Products placed further apart in this space are perceptually more different from products found closer together (Coxon, 1982; Shiffman, Reynolds, & Young, 1981).

With the attribute rating analysis (ARA), care must be taken to ensure that attribute set is complete (Pessimier, 1975). This is of particular concern since information loss may occur if a critical attribute is omitted

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(Steenkamp et al., 1994). This loss remains unnoticed unless the study is repeated including this critical attribute.

When using a prespecified attribute set the following assumptions are made: (1) All attributes in the questionnaire are relevant to each consumer, (2) Attributes relevant to each consumer have been included and (3) The meaning of an attribute is universal (Steenkamp et al., 1994). Individual differences such as experience with the products and personality differences may cause consumers to differ in the number of attributes used to describe a product category (Aronson, Wilson, & Akert, 1994; Steenkamp et al.). It is also possible that consumers use the same attribute in different ways (Steenkamp et al.).

A number of British researchers (examples are: Langron, 1983; Thompson & MacFie, 1983; William & Arnold, 1984; Williams & Langron, 1984) proposed using an alternate profiling method, free-choice profiling (FCP), with consumers to overcome some of the above assumptions. Free-choice profiling allows consumers to describe and evaluate brands in their own terminology. Each consumer's evaluations are transformed into individual configurations. These individual configurations are compared using generalized Procrustes analysis (GPA) to obtain a group space (perceptual map). GPA allows one to compare consumers perceptual homogeneity—in terms of word choice and in terms of perceived relationships among products.

The dimensions of the consensus space are interpreted by examining the correlations of each individual consumer's attributes with the dimensions of the group consensus (Steenkamp et al., 1994). Attributes with higher correlations that lay close to a particular dimension are more significant in describing that dimension.

The two profiling methods, ARA and FCP, differ in information collection and analyses, yet both yield a perceptual map. The objective of this project was to compare the perceptual maps of attribute rating analysis and free-choice profiling of photographs of carbonated beverage brands using consumers.

2. Materials and methods

2.1. Participants

A total of 86 subjects participated in this test. Forty-two and 44 subjects participated in ARA and FCP, respectively. All subjects were students at the University of Missouri-Columbia between the ages of 18 and 34. Participation was voluntary.

2.2. Materials

Photographs of 12 oz aluminum cans of 12 carbonated beverages were evaluated (Caffeine-Free Coca-Cola®, Coca-Cola Classic®, Diet Coke®, Caffeine-Free Diet Coke®, Cherry Coke®, Diet Cherry Coke®, A and W Rootbeer®, Dr. Pepper®, RC Cola®, Shasta Cola®, Mountain Dew® and Diet Mountain Dew®). The specific brands were chosen based on high product usage in vending machines and retail sales on the University of Missouri campus and in the city of Columbia, MO. All panelists had consumed all soda brands at least once. Coca-Cola® products were chosen to represent branded "regular," sugar-free, caffeine-free and diet caffeine-free colas. Subjects were presented color photographs of single 12 ounce cans of the beverages before rating the products. No coding of the beverages was employed.

2.3. Procedure

For ARA, 42 subjects (25 males and 17 females) were presented color photographs of the beverages, then asked to evaluate the beverages in random order. Each beverage was rated on 13 specific attributes (Table 1), these attributes were determined in a preliminary study with 10 students, who did not take part in the final ARA. All attributes were rated using a 10.3 cm bipolar unstructured line scale anchored on the left with "strongly disagree", on the right with "strongly agree" and in the middle with "neither agree nor disagree." Product evaluations were completed in two, 15–20 min test sessions.

For FCP, 44 subjects (22 males and 22 females), who did not participate in the ARA method were presented individual color photographs of the beverages and asked to divide them into two groups specifying the criterion used for the partition. This task was repeated until no additional subdivisions were identified. The subjects were then asked if they would consider additional criteria when evaluating the brands not identified by the previous exercise. Once relevant attributes were identified, subjects placed the various criteria generated for each brand on the evaluation sheet. This methodology is more structured than a typical FCP, in fact it had some relationship to the repertory grid method although it was not as structured as that technique (Lawless & Heymann, 1998; McEwan, Colwill, & Thompson, 1989; Piggott & Watson, 1992). The criteria were rated on a 10.3 cm bipolar unstructured line scale with the same anchors as with the ARA profiling. The 12 beverages were evaluated in random order. Due to the individual attention required for each subject, evaluations were completed separately. Each individual session took approximately 15 to 25 min.

2.4. Data analysis

The perceptual map for the ARA data was derived by PCA. The raw data set was analyzed using the PROC FACTOR procedure in SAS® with varimax rotation,

Table 1
Attributes evaluated by ARA subjects[a]

Is consistent in quality time after time	Has a flavor I like a lot
Is fun to drink	Is good product for the whole family
Is good product for female adults	Is good product for male adults
Is good product for teenagers	Is good product for children
Is fresh	Is a brand I can trust
I like the package it comes in	Is a good value
Is often on sale or has coupons	

[a] Scale: "Disagree" = 0, "Neither agree nor disagree" = 5.15 and "Agree" = 10.3.

using the correlation matrix. We chose to use the correlation matrix which standardizes the individual data rather than the more usual covariance matrix which does not because we were going to compare the PCA results to the GPA results which would have been standardized. Since all FCP consumers did not use a consistent set of attributes to describe differences among brands, it was not possible to use PCA. Therefore, a consensus configuration for the FCP data was derived using "classical" GPA based on the method of Gower (1975) [the program used was Procrustes PC v2.2 (Oliemans, Punter & Partners, 1991)]. The resulting product spaces (configurations) were compared for similarity. To investigate the similarity of the two configurations, the product loadings of the first four dimensions in the ARA and FCP data were correlated using the PROC CORR procedure in SAS®. GPA was also used to match the two data sets into a consensus space (Oliemans et al. 1991).

3. Results and discussion

3.1. Attribute rating analysis (ARA)

Principal component analysis simplified the interpretation of the product evaluations by reducing the original attribute set to a low-dimensional space. Based on the eigenvalues (greater than 1), scree plot of the eigenvalues versus component extracted and variance explained, a four-dimensional perceptual map was used. Seventy-four percent of the total variance was explained by the four-dimensional space. The first principal component (PC) accounted for 41% of the total variance, whereas PC2, PC3 and PC4 explained 15, 10 and 8%, respectively.

Loadings of the attributes and sample factor scores for PC1 versus PC2, for PC1 versus PC3 and for PC1 versus PC4 are shown in Figs. 1–3, respectively. Larger loadings suggest a stronger correlation with a factor. An attribute was considered significant if the factor loading was greater than 0.39. This was based on the guideline provided by Stevens (1986, p. 345) where he stated that an attribute should share at least 15% of its variance with the specific PC to be used in interpretation. All attributes evaluated had loadings higher than 0.39 on one or more dimensions. Most of the attributes had loadings exceeding $|0.70|$ on a single dimension. By examining these "heavy" loadings ($>|0.70|$) and sample scores on the dimensions, descriptors for each PC were determined.

The first PC was heavily loaded by the "Is good for..." attributes and the PC was labeled "general quality". The second was interpreted as "consistent/ trusted", based on the loadings, PC 3 was a "fun to drink/ liked flavor" dimension based on the loadings and based on the factor scores it also separated diet sodas from non-diet sodas and it was thus labeled a "diet" dimension. Based on the loadings PC4 was heavily loaded with "have coupons/is a good value" and was labeled the "value" dimension.

3.2. Free-choice profiling (FCP)

Subjects completing FCP used 4.7 attributes, on average, to describe differences among the samples. The number of attributes ranged from two to eight and the distribution was 2(2), 3(3), 4(16), 5(12), 6(7), 7(3) and 8(1). An initial GPA using all subjects had two dimensions. For comparison to PCA, a four-dimensional consensus space or map was of interest. To obtain a four-dimensional space, individuals with two or three descriptors were eliminated from the data set submitted to GPA. Thus, the data from 39 subjects (19 males and 20 females) were used. The fit value and Procrustes least square loss for this space was 1.55 and 35.878, respectively. The assessors' residuals ranged from 0.486 to 1.373. Based on data by King and Arents (1991), a true consensus configuration at $\alpha = 0.05$ was obtained based on the R_c value of 60.4%. The first four dimensions accounted for 60% of the variation associated with the samples. Dimension one explained 26% of the variation in the samples, while the second, third and fourth dimensions explained 18, 11 and 5% of the variation, respectively. The two dimensional GPA with all the subjects (not shown) was very similar to the first two dimensions of the four dimensional GPA performed with 39 subjects. Therefore, we will only describe the four-dimensional GPA in the rest of this paper.

Figs. 4–6 show the attribute correlations to the Procrustes dimensions for six randomly chosen consumers and the sample consensus coordinates for the sodas for Dimension 1 (Dim 1) versus Dim 2, Dim 1 versus Dim 3 and Dim 1 versus Dim 4, respectively. To interpret and label the dimensions, individual attribute correlations to the dimensions were evaluated for all 39 consumers. Attributes with longer vectors (correlations) which lay close to a particular dimension assisted in describing the

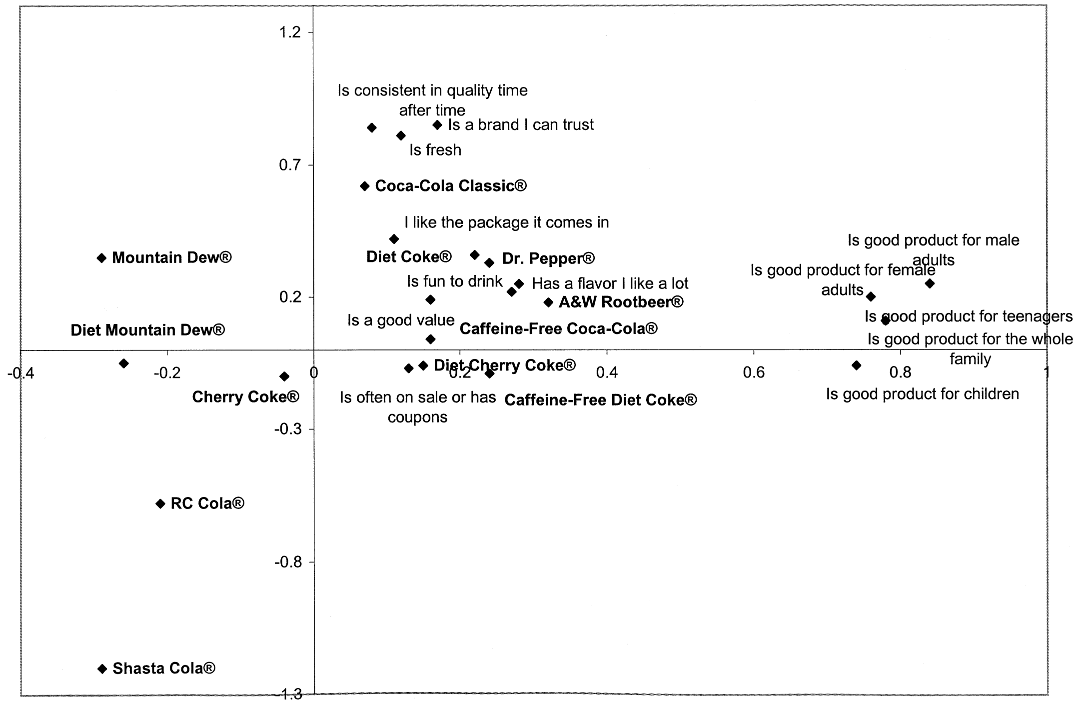

Fig. 1. Principal Component (PC) plot for PC1 and PC2 of the Attribute Rating Analysis of photographs of soda brands. PC1 accounted for 41% of the variance and PC2 for 15%. Soda factor scores are in bold-face font; attribute loadings are in regular font.

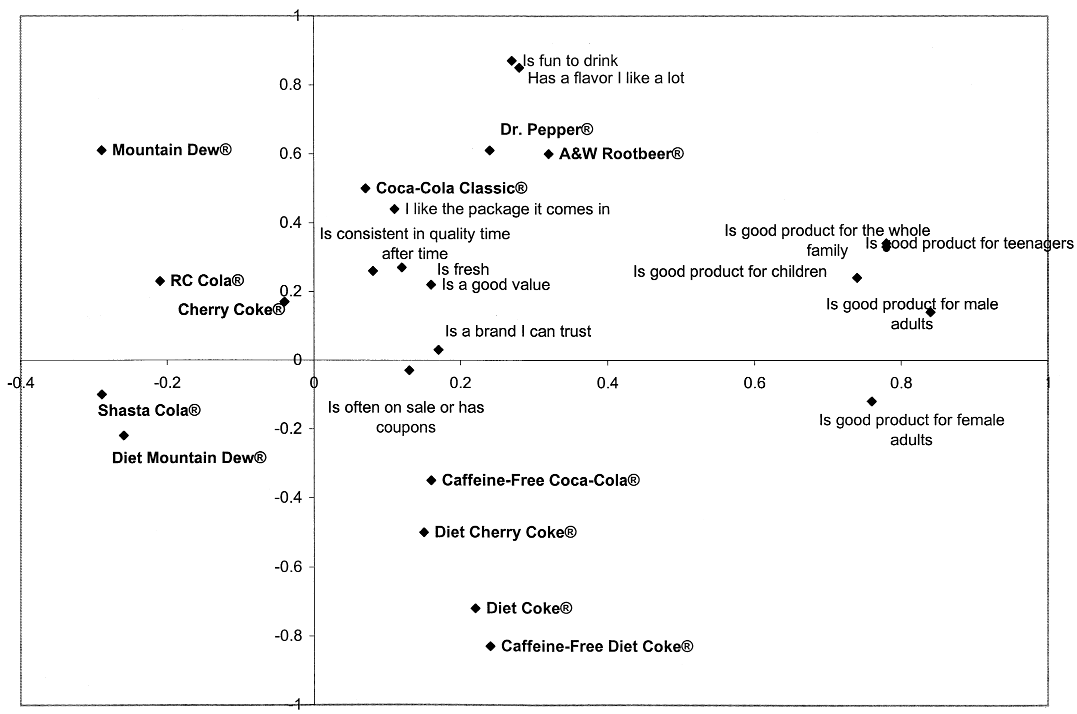

Fig. 2. Principal Component (PC) plot for PC1 and PC3 of the Attribute Rating Analysis of photographs of soda brands. PC1 accounted for 41% of the variance and PC2 for 10%. Soda factor scores are in bold-face font; attribute loadings are in regular font.

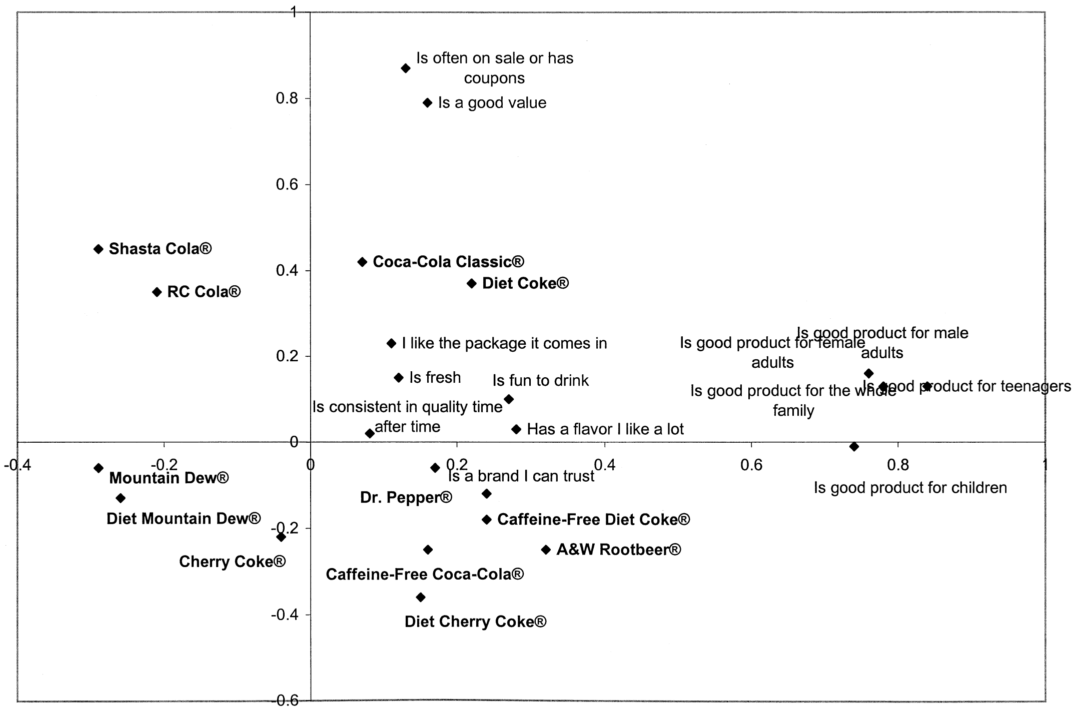

Fig. 3. Principal Component (PC) plot for PC1 and PC4 of the Attribute Rating Analysis of photographs of soda brands. PC1 accounted for 41% of the variance and PC4 for 8%. Soda factor scores are in bold-face font; attribute loadings are in regular font.

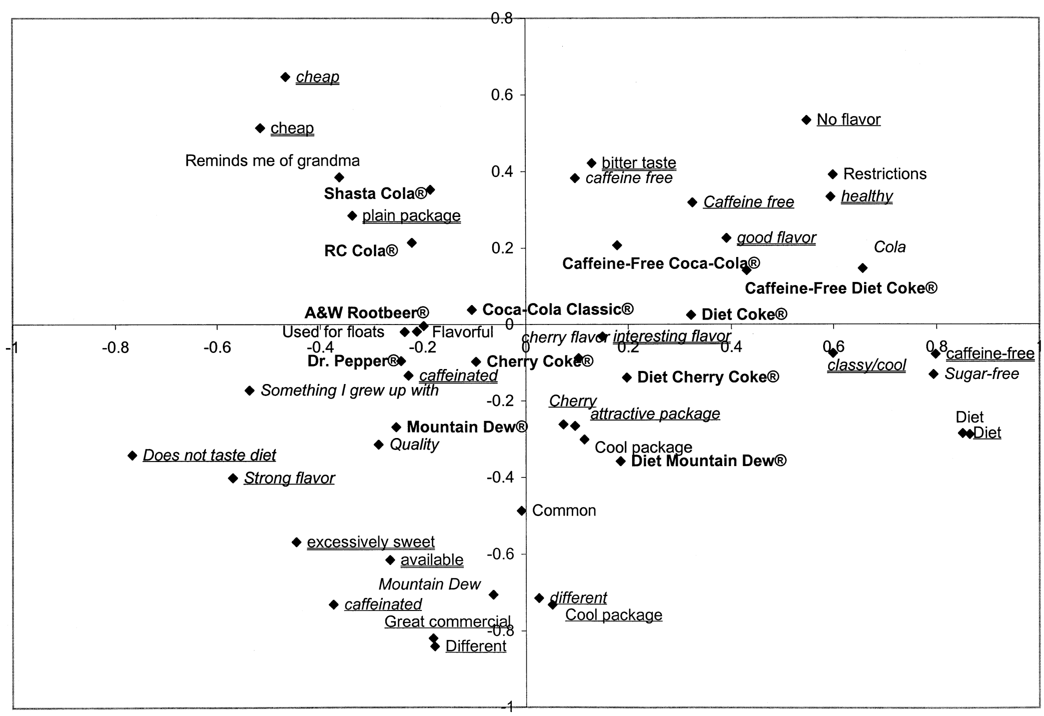

Fig. 4. Generalized Procrustes plot for Dimension 1 (Dim1) and Dim 2 of the Free Choice Profiling of photographs of soda brands. Dim 1 accounted for 26% of the consensus variance and Dim2 for 18%. Soda consensus coordinates are in bold face font; six randomly chosen consumers' attribute correlations are in italics, regular font with and without underlining.

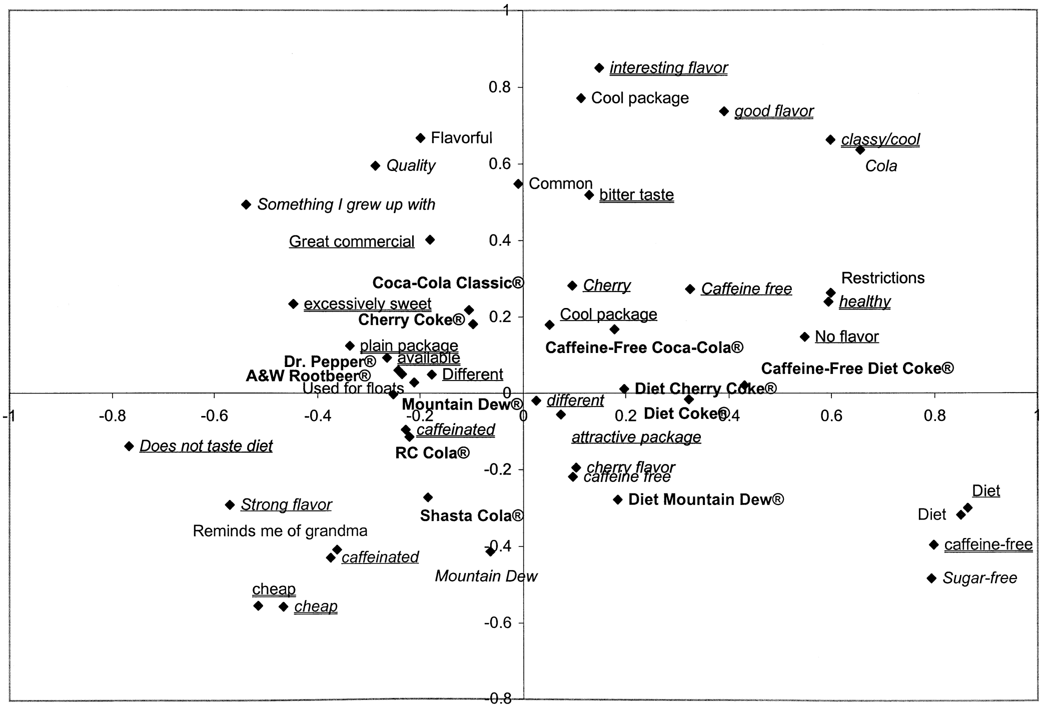

Fig. 5. Generalized Procrustes plot for Dimension 1 (Dim1) and Dim3 of the Free Choice Profiling of photographs of soda brands. Dim1 accounted for 26% of the consensus variance and Dim3 for 11%. Soda consensus coordinates are in bold-face font; six randomly chosen consumers' attribute correlations are in italics, regular font with and without underlining.

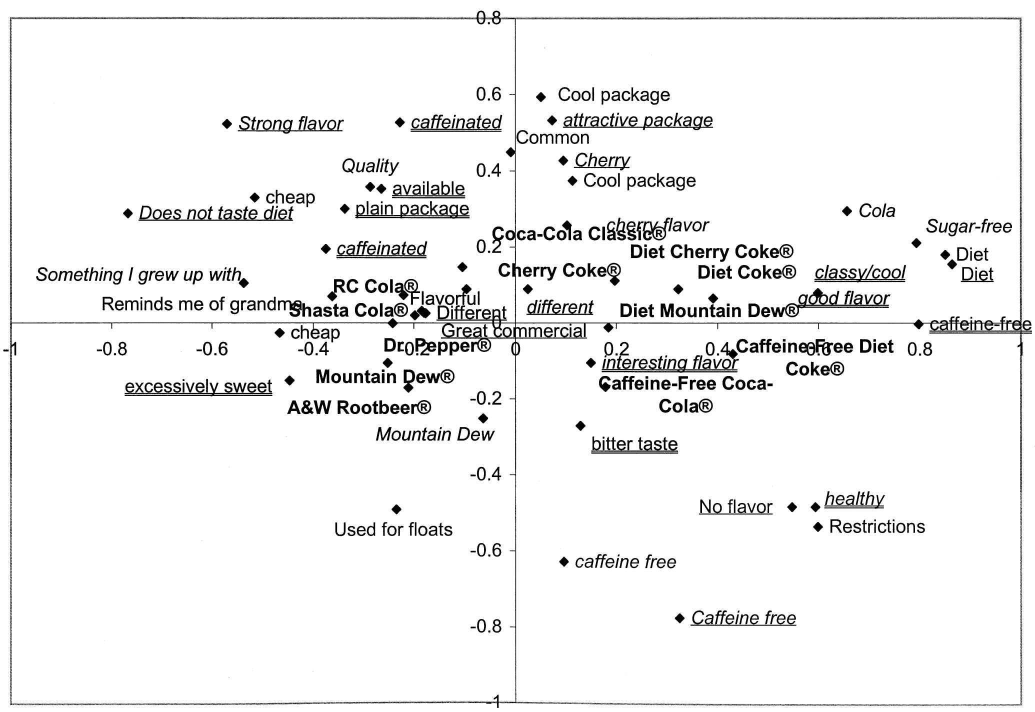

Fig. 6. Generalized Procrustes plot for Dimension 1 (Dim1) and Dim4 of the Free Choice Profiling of photographs of soda brands. Dim1 accounted for 26% of the consensus variance and Dim4 for 5%. Soda consensus coordinates are in bold-face font; six randomly chosen consumers' attribute correlations are in italics, regular font with and without underlining.

respective dimensions. In general, dimension one was described by terms related to being "diet", "sugar-free" or "overly sweet", "does not taste diet" (negatively related). The second dimension was positively loaded with "cheap", "uncommon" and negatively with "common" "cool package", "great/cool commercial". There was less agreement on the terms that were heavily loaded on the third and fourth dimensions. It appeared the third dimension may be related to "soda type" (i.e. cola, flavored cola or not a cola). Finally, the fourth dimension may be related to the perceived level of caffeine due to terms related to "caffeine-level" being weighted heavily on this dimension. The consensus coordinates for the samples appear (Table 4), to contradict this dimension title. Mountain Dew®, a highly caffeinated product, was weighted similar to Caffeine-free Diet Coke® on dimension four. However, it is possible that some consumers may not know that Mountain Dew® is caffeinated, although in Dimension 3 "Mountain Dew" and "caffeinated" were loaded together. This anomaly may also be due to the very low amount of variance (5%) described by Dim 4.

3.3. Comparison of ARA and FCP

3.3.1. Correlations

The correlations of the sample factor scores and sample consensus coordinates on the four dimensions of the perceptual maps for ARA and FCP, respectively, are in Table 2. The first dimension of the ARA perceptual map was strongly correlated with the third dimension of the FCP perceptual map. The remaining significant correlations were not as high. PC2 of the ARA perceptual map was also correlated with the second FCP dimension. Dimension three of ARA was correlated with dimension two and three of FCP. Although not significant, dimension four of the FCP and ARA appeared to be related. All significant correlations between the ARA and FCP dimensions generally agreed with the subjective names. For example, ARA3 labeled as "diet" was significantly correlated with the FCP dimensions labeled as "diet" (FCP2) and "common/cheap" (FCP3). The significant correlation with FCP3 may be because the diet beverages evaluated were national brands that are widely distributed ("common") and regularly on sale ("cheap").

Table 2
Correlation of FCP consensus coordinates and ARA factor scores[a]

Element	ARA1 "General Quality"	ARA2 "Consistent"	ARA3 "Diet"	ARA4 "Value"
FCP-1 "Diet"	0.27 (0.40)	0.17 (0.59)	**0.57 (0.05)**	−0.29 (0.36)
FCP-2 "Common," "Cheap"	0.10 (0.75)	**−0.57 (0.05)**	**0.67 (0.01)**	−0.04 (0.90)
FCP-3 "Quality"	**−0.92 (0.0001)**	−0.23 (0.47)	0.20 (0.54)	−0.09 (0.79)
FCP-4 "Caffeine-level"	−0.22 (0.48)	0.48 (0.12)	−0.27 (0.39)	0.50 (0.10)

[a] The p-value for each correlation is in parentheses beside the respective correlation. Significant p-values ($p \leqslant 0.05$) are shown in bold.

3.3.2. Generalize Procrustes analysis

Generalized Procrustes analysis (GPA) was used to match the ARA and FCP configurations and resulted in a consensus space. The resulting fit value and Procrustes least square loss for the consensus space was 45.63 and 8.73, respectively. The R_c value (91.27%) suggests that a true consensus configuration at $\alpha = 0.05$ was obtained based on the data of King and Arents (1991). Ninety-one percent of the consensus variation associated with the samples was accounted for by four dimensions. Dimension one explained 42% of the variation in the samples, while the second, third and fourth dimensions explained 30, 12 and 7% of the variation, respectively. The large consensus variance suggests that very little information loss occurred due to GPA. Therefore, the two individual spaces were similar.

To understand the consensus dimensions further, the consensus coordinates of the original dimensions in the consensus space were investigated (Fig. 7). There were negative relationships between ARA3 and FCP1 on Dim 1, and this differed from the correlation analysis where ARA3 and FCP1 were positively correlated. For dimensions two, three and four the results were not as clear. On Dim 2 FCP3 and ARA2 were positively related as were FCP2 and ARA4, yet on Dim 3 ARA1, FCP3, FCP2 and ARA4 were related.

3.3.3. General considerations

With both methods, interpreting the dimensions was subjective. From the investigator's point of view, for these samples it seems that the FCP method was better at discerning the underlying perceptual dimensions. With FCP, the vocabulary used to describe differences in the products was generally much more explicit than the terms used in ARA. This could have been prevented by using a more explicit set of ARA attributes, yet in the preliminary study the consumers were not as explicit. This is likely a function of how the FCP attributes were derived. Consumers had to describe criteria to differentiate among the samples in a very structured way whereas in the ARA preliminary study consumers simply listed attributes.

The explicit FCP attributes would typically be advantageous when interpreting the dimensions. Since the loadings of terms were not typically weighted heavily on one dimension, the advantage gained was relatively small for these samples.

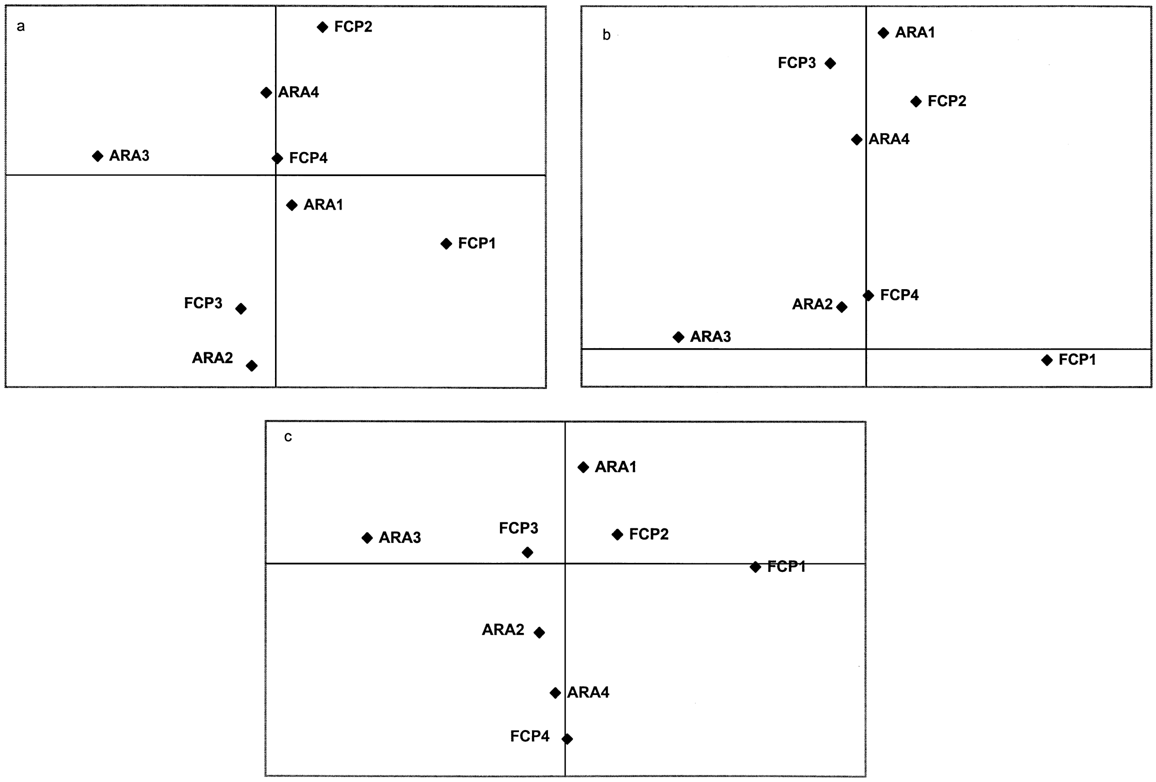

Fig. 7. Generalized Procrustes plot of the Attribute Rating Analysis principal components and of the Free Choice Profiling dimensions: (a) Dimension 1 (Dim1) accounted for 42% of the consensus variance and Dim2 for 30%; (b) Dimension 1 (Dim1) accounted for 42% of the consensus variance and Dim3 for 12%; (c) Dimension 1 (Dim1) accounted for 42% of the consensus variance and Dim4 for 7%.

Free-choice profiling does not require the initial commitment of resources to identify attributes required for ARA. This is commonly used as justification for FCP. While ARA may require initial resources, it does not require the time commitment required for each individual participant as with FCP. Specifically, one-on-one attention must be given to each panelist to identify their attributes and transfer these to the appropriate score sheets. In addition, the data analysis is much more time consuming with FCP, than with ARA.

4. Conclusions

Based on the analysis of this study the FCP perceptual map appeared similar to the perceptual map derived from ARA. Dimensions from the two methods were significantly correlated. Besides similarity of the resulting maps, neither method appeared better at discerning the underlying factors of the perceptions for the various dimensions. Therefore, the method choice should be based on the specific needs of the situation. If a thorough understanding of a product category exists, completing FCP would appear unwarranted. In this situation a comprehensive attribute set may exist or could easily be developed. On the other hand, if a limited understanding of a product set exists such as when entering a new product category, completing FCP might be suggested. In this case, FCP profiling would not only result in producing a perceptual map, but also provide an initial understanding of the attributes important to the product set. In this particular set we feel that the attributes derived by FCP probably were much more comprehensive than the ARA attributes, with the result that the FCP gives a more real indication of consumers' of the soda brands when evaluating photographs of soda cans.

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