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Consumer-Based Product Profiling: Application of Partial Napping® for Sensory Characterization of Specialty Beers by Novices and Experts

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Napping® is an inexpensive and rapid method for sensory characterization, suitable for both trained and untrained subjects. In the study presented, the method was applied on 9 specialty beers. Subjects were 17 consumers without any training as sensory panelists, of whom 8 were beer experts and 9 novices. The aim was to explore the usability of the Napping® method by untrained consumers and to analyze differences between beer novices and experts in their ability to discriminate and describe the products. The method succeeded in discriminating between the beers, revealing sensory descriptors responsible for the differences. Analysis of differences between the two groups showed that the experts had higher agreement with regard to sample differences (significantly higher mean RV-coefficient, 0.61 vs. 0.41 for non-experts, p = 0.013). The results support the usability of Napping® as a fast method for sensory characterization, with the advantage of providing a product characterization based on consumer descriptions, thus better reflecting consumers' experience with the product.

KEYWORDS Napping, beer, fast sensory methods, sensory profiling, consumers vs. experts

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INTRODUCTION

Sensory profiling, i.e., the process of measuring and describing food product characteristics as perceived by the human senses, is traditionally performed by trained assessors. However, in the last two decades, there have been increasing attempts to use consumers for descriptive tasks (Schutz, 1999). A variety of methods have been developed to collect information about product characteristics that rely directly on consumers' perceptions. From this perspective, the rise of so-called rapid sensory descriptive methodologies is a major step forward toward usability of consumer data. The broad definition of fast sensory methods encompasses a variety of methods, such as Free Choice Profiling (Williams & Langron, 1984; Jack & Piggott, 1992), Projective Mapping (Risvik, McEwan, Colwill, Rogers, & Lyon, 1994), Napping® (Pagès, 2005), Flash Profile (Dairou & Sieffermann, 2002), and Sorting Task (Abdi, Valentin, Chollet, & Chrea, 2007).

These methods, which share a common rationale, aim at targeting two important drawbacks of conventional sensory profiling technique: on the one hand, although conventional profile undoubtedly remains the most accurate method for product characterization, training the assessors to precisely quantify the sensory characteristics of interest requires time and some money (Chollet, Lelièvre, Abdi, & Valentin, 2011). On the other hand, there is the risk that assessors will experience the product differently from consumers or that they take into account sensory attributes that are not relevant for consumers (Ares, Deliza, Barreiro, Gimenez, & Gámbaro, 2010). Therefore, there are pressures from the industry to develop fast methodologies that allow cost reduction—an issue particularly important for SMEs—while at the same time ensuring that the obtained sensory data reflect consumers' experience.

In this study, we present an application of a specific fast sensory method—partial Napping®—on a product set of 9 special beers, using subjects with different degrees of expertise with the product. This article discusses the results obtained and illustrates how partial Napping can be used as a fast and inexpensive method for collecting information about food products.

Fast Methods to Obtain a Product Map

One of the first "fast sensory methods" to appear in the literature was Free Choice Profiling (FCP; Williams & Langron, 1984), a method that introduced the idea of having panelists developing their own words to describe sensory stimuli and using these descriptors to rate a set of food products. The data obtained can be manipulated by Generalized Procrustes Analysis (GPA; Gower, 1975) to obtain an overall product map showing relationships between the samples. By having people using their own words to describe food products (rather than a standardized vocabulary framed by the experimenter or the panel leader), FCP was the first attempt to develop a method suitable for untrained subjects, and it represents a viable method of gaining insights into consumer perceptions (Jack & Piggott, 1992).

Projective mapping (Risvik et al., 1994) was the first method to introduce the idea of expressing differences between products as geometric distances in a given space. In the original version of this methodology (Risvik et al., 1994), assessors are presented with all products at the same time and required to place products on a surface (such as a blank sheet of paper) according to how different or similar they perceive them to be related to each other. The result is a perceptual map in which close samples represent similar products and, conversely, samples far away from each other represent different ones. The data are quantified using a coordinate system, and a consensus product configuration is obtained after performing GPA on the map coordinates for each individual.

This method did not gather much attention until recent years, when it was re-proposed by Pagès (2005) in its “Napping” version (the name comes from the word *nappe,* French for “tablecloth”). Napping can be considered a special sub-case of projective mapping, and it contains some important additions to the original projective mapping with regard to both the materials used and the statistical analysis performed (described in the following sections).

Aims of the Study

Napping has already found applications in a number of published studies with many different products (for an overview, see Lawless & Heymann, 2010, pp. 461–462), but mostly performed by trained sensory panelists, and never with beer as a case study. Thus, the present study had two main aims:

1. Explore whether Napping—performed by untrained subjects—would succeed in *describing* and *discriminating* between nine Danish special beers. In other words, we wanted to check whether we would get an interpretable sensory profile of the nine beers. This objective was exploratory in nature, with a focus on interpretability rather than statistical significance;
2. Test differences between two distinct groups of subjects—beer novices and experts—with regard to their ability to discriminate and describe the set of beers. We hypothesize that experts would discriminate the product more consistently than novice consumers. This can be tested statistically by looking at the *RV* coefficient (a measure of fit between two configurations; further explanation in the followings) of the individual panelist and comparing the results from the two groups. Thus, our hypothesis can be formalized as follows:

$$H : \overline{RV}_{Experts} > \overline{RV}_{Novices}$$

and the null hypothesis as

$$H_0 : \overline{RV}_{Experts} \approx \overline{RV}_{Novices}$$

MATERIALS AND METHODS

The Beers

Nine special Danish beers—seven commercially available and two experimental—were chosen for this study. The selection was made in order to ensure enough variety between the samples and to illustrate current tendencies of beer making in Denmark. Moreover, each of them contained a special ingredient or flavor of interest to add more complexity to the discriminative task. The full list of the beer samples is given in Table 1.

Subjects

Subjects ($N = 17$) were recruited through the authors' personal network. Roughly half of them ($N = 8$) were professional brewmasters or very knowledgeable beer consumers (named "experts" throughout this article), whereas the others ($N = 9$) were novice consumers with an interest in beer. None of them had ever undergone any sensory training in the description of beer flavors; however, it seemed sensible to assume a higher general experience with the product in the expert group compared to the novices.

TABLE 1 List and Details of the Beer Samples Used for the Study

Beer name	Brewery	Beer type*	Special flavor
Nutty	Ørbæ Bryggeri	Brown Ale	Walnuts
Fynsk Forår	Ørbæk Bryggeri	Pale Ale	Elderflower
Havre Stout	Bryggeri Skovlyst	Stout	Oat and rye
Classens Lise	Halsnæs Brygus	Pale Ale	Chamomile and heather (*Calluna vulgaris*) honey
Enebær Stout	Grauballe Bryghus	Stout	Juniper berries
Bøgeberg	Bryggeri Skoviyst	Amber Ale	Beech twigs
Oak Aged Cranberry Bastard	Hornbeer	Fruit Beer	Cranberries
Rosehip Beer	Experimental	Pale Lager	Pilsner beer ("Grøn Tuborg") with added rosehip powder[1]
Pine Beer	Experimental	Pale Lager	Pilsner beer ("Grøn Tuborg") with added pine needles flavorant[2]

[1]"Hybenpulver Økologisk," Coesam SA Laboratorios de Cosmetica. Concentration = 5% (5 g/95 g).
[2]"Pin Thyrol," Firmenich SA. Concentration = 0.00625% (6.25 ul/100 ml).
*Self-reported by the producer.

Experimental Procedure—*Partial Napping*

The presented study was conducted in two identical experimental sessions.

All the beer samples were presented simultaneously to the subjects, blind labeled with a three-digit code. They were served at temperature of 8°C in clear glasses. Approximately 5 cl of each beer was given to the subjects.

For the Napping task, subjects were provided with a large sheet of blank paper: the tablecloth, or *nappe*. We used the indication of Pagès (2005), a 60 cm × 40 cm white sheet with no coordinates drawn.[1] Subjects were instructed to smell and taste the samples one by one, then place them onto the tablecloth in a way that reflected the perceived similarities or differences: similar samples should be placed very near, and different samples should be placed distant from each other (Pagès, 2005).

Furthermore, it was explained to the subjects that they were free to choose their own criteria to place the samples on the sheet, and that there were no right or wrong way of doing it. We did introduce one limit, however: i.e., subjects were instructed to focus solely on smell and taste characteristics and not to consider appearance and mouthfeel. This kind of Napping task, focused on a limited number of sensory dimensions, is known as "partial Napping" or "Napping by modality" (Pfeiffer & Gilbert, 2008) and was originally proposed by Pagès (2003). Compared to its holistic version, partial Napping allows the subjects to be more analytical (Pfeiffer & Gilbert, 2008). In the present study, the sample set had rather large visual differences that were irrelevant to the flavors, thus the restriction to focus on smell and taste. Furthermore, on comparative studies, partial Napping has been found to give the closest results to those of conventional profiling (Dehlholm, Brockhoff, Meinert, Aaslyng, & Bredie, 2012), supporting the reliability of this method (Pfeiffer & Gilbert, 2008).

When the discriminative task was completed, subjects were instructed to write down on the tablecloth the number of each beer sample in the place they occupied. At this point, the Napping was combined with an Ultra-Flash Profiling (UFP; Perrin et al., 2008) task: i.e., the subjects were asked to write down (directly on the sheet) any word they found appropriate to describe each sample. A completed *nappe* consists of marks indicating the position of each sample plus, next to each of them, the descriptors used for that particular sample.

The combination of Napping and UFP has been used by some authors, and these two techniques have proved to be good complements for each other (Albert, Varela, Salvador, Hough, & Fiszman, 2011; Perrin et al., 2008; Pfeiffer & Gilbert, 2008). Through ad hoc multivariate statistical analysis, Napping and UFP together can provide a quick profile showing relationships

[1] Unlike the original Projective Mapping technique, where an A4 sheet with two crossed axes was used (Risvik et al., 1994).

between products and descriptors, similar to Principal Component Analysis (PCA) results from conventional profiling (Pfeiffer & Gilbert, 2008).

DATA TREATMENT

Data were digitalized using a coordinate system with the origin in the left bottom corner. The outcome was a table with 9 rows (the samples) and 34 columns (the X and Y coordinates for each subject).

The descriptors—i.e., the words elicited during the ultra-flash profiling part—were entered separately and treated as a contingency table crossing products and descriptors.

Because of the large number of terms generated during the descriptive task (no restrictions on neither type or number on words that could be used), synonyms or near synonyms were semantically clustered prior to the analysis. This was done qualitatively, with the help of two "institutional" tools: the "beer flavor wheel" (Meilgaard, Dalgliesh, & Clapperton, 1979) and the "Danish Beer Language" (Det Danske Ølakademi, 2006). Furthermore, words mentioned only once were not included in the analysis.

Statistical Analysis

All statistical analyses were performed using the computing environment R (R Development Core Team, 2005) and the R packages SensoMineR (Lê & Husson, 2008) and FactoMineR (Lê, Josse, & Husson, 2008).

Procrustes Multiple Factor Analysis

The data were analyzed by Procrustes Multiple Factor Analysis (PMFA) (Morand & Pagès, 2006). As the name suggests, this method combines Multiple Factor Analysis (Pagès & Husson, 2001) and Generalized Procrustes Analysis (Gower, 1975). It consists in creating an MFA consensus configuration from each subject's sheet (Morand & Pagès, 2006), thus being particularly suitable for a Napping task, in which product sensory differences are expressed as Euclidean distances.

The analysis is performed in three steps. First, an initial PCA is performed on the individual configurations where each product sample has X and Y coordinates. These data are then normalized by dividing all the elements by the first eigenvalue obtained on this PCA. Second, the normalized individual data sets are merged into a global matrix, and a new PCA is performed on the new matrix. The scores plot of this new PCA represents a sort of consensus map of how the panel perceived the products on a global level. Finally, each individual configuration undergoes a procrustean rotation and is superimposed to the global configuration, in order to allow comparisons between the individual configurations and the global ones. This can be done by computing the *RV* coefficients, which is a statistical measure of fit between two configurations (see next section). Thus, PMFA allows for comparison between individual and consensus configuration, which can be used to gather various insights.

The descriptors (i.e., the words elicited during the ultra-flash profiling task) are used as a set of supplementary variables, meaning that they do not influence the factors (i.e., the axes) construction, but their correlation coefficient with each factor is calculated and represented visually as in a loadings plot of a PCA model (Perrin et al., 2008).

The use of MFA for handling Napping data was one of the most important additions introduced by Pagès (2005) to the original projective mapping technique. The main advantage of employing MFA for this kind of data is that this method (as opposed to previously employed methods, e.g., PCA) treats each individual as a group of two un-standardized variables (the X and Y coordinates) (Pagès, 2005). This is important because individual differences in the use of the space (vertical vs. horizontal dimension) are respected, whereas in a standardized PCA this initial configuration would be deformed (Morand & Pagès, 2006), and thus it is possible to see what is actually important for that person (Lawless & Heymann, 2010). Furthermore, MFA balances the various groups (i.e. the subjects) as explained earlier,[2] ensuring that no group plays a predominant role in the first two dimensions of the consensus configuration.

After the PMFA model was calculated, Agglomerative Hierarchical Clustering (AHC) was performed on the data to obtain a tree of similarity and differences between the samples based on their scores on the MFA dimensions (Husson, Lê, & Pagès, 2011). This clustering technique uses Ward's agglomerative algorithm to progressively regroup elements in a Euclidean space (in this case, the consensus profile), looking at clusters inertia as a measure of variability. By adding more dimensions, and thus more inertia, the number of clusters decreases and within cluster inertia increases, until all the individuals are in the same clusters (Husson et al., 2011). In our case, samples are defined by quantitative variables (their scores on the progressive MFA dimensions), thus, clustering was performed with an equation similar to that of an *n*-way ANOVA (with clusters as objects and dimensions as treatment). The optimal number of clusters was obtained by minimizing the following criterion:

$$\min_{q_{\min} \leq q \leq q_{\max}} \frac{\Delta(q)}{\Delta(q+1)},$$

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2 In the version used for this study—which is the one proposed by the method developers (Pagès & Husson, 2001; Pagès, 2005)—the scaling factor is the first eigenvalue of a separate PCA performed on each individual configuration.

where $\Delta(q)$ is the between-clusters inertia increase when moving from q – 1 to q clusters, $q_{\min}$ and $q_{\max}$, respectively, the minimum and maximum number of clusters chosen by the users (Husson et al., 2011).

RV Coefficients

The *RV* coefficient (Robert & Escoufier, 1976) is a measure of similarity between two set of points. Its value is comprised in the closed interval [0,1]: the closer it is to 1, the more similar the two configurations will be. Computing *RV* coefficients in a Napping test can provide very useful indications. For instance, if the test is done with trained assessors, it can provide a measure of a panelist's performance compared to the group.

In the present context, we used mean *RV* coefficient for beer experts and novices to test differences between these two groups. *RV* coefficients for subjects in both groups were computed, and *t*-test on the group means to uncover whether real differences existed, allowing us to test our hypothesis that experts would give a more consistent profiling than the novices.

Figure 1 gives an example of the consensus configuration with an individual tablecloth superimposed.

RESULTS

The PMFA conducted yielded five main representations of our dataset: (1) a consensus profile of the 9 beers; (2) a representation of the X and Y dimensions of each tablecloth and their relations with the MFA dimensions; (3) a representation of the descriptors used by the subjects to describe the beers; (4) individual profiles of the 9 beers by each panelists; (5) individual profiles superimposed to the consensus one (as exemplified in Figure 1).

Each of them can provide different insights, as we show in the following sections.

Consensus Profile of the 9 Beers

The consensus product map (Figure 2), is obtained only from the Napping data. This plot shows how the subjects perceived the beers relative to each other on an overall level: the closer the two beers, the more similar, and the further apart, the more different. The first two dimensions combined explain 55.3% of the total variance in the data set. Most of the beers are distributed along the first dimension, whereas the second dimensions mostly described the specificity of one particular sample (Oak Aged Cranberry Bastard), and, to a lesser extent, highlighted further differences by spreading some of the other beers apart. The scree plot suggested that two components were optimal. However, adding a third dimension (with a total of 67.1% total

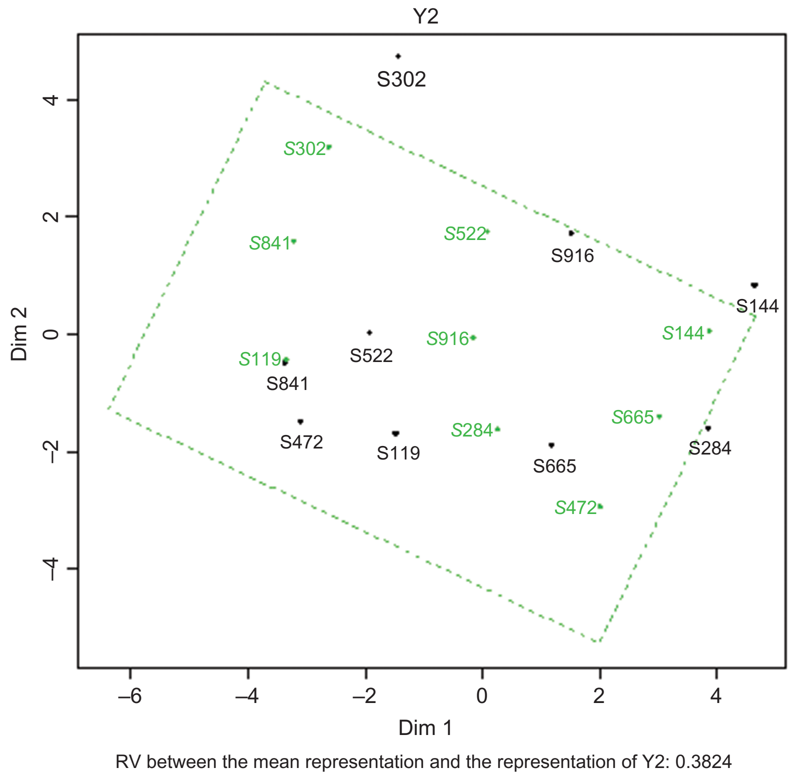

FIGURE 1 Consensus configuration (black) with an individual tablecloth superimposed (green, Subject Y2). Note the procrustean rotation (to maximize similarity). The computed *RV* coefficient on the bottom gives a measure of the similarity between the two configurations. For brevity, samples are labeled with 3-digit codes at this stage (color figure available online).

variance explained) further explained the specificity of Classens Lise, already recognized as different in the first two dimensions.

The agglomerative Hierarchical Clustering showed that the nine samples were located in seven distinct clusters. Samples that are not significantly different from each other are grouped by ellipses in Figure 2—Cluster 1: Havre Stout and Enebær Stout; Cluster 2: Bøgebryg and Nutty—i.e., all the beers expect the ones clustered were perceived as different by our panel ($p < 0.05$).

To elaborate on the consensus profile, the configuration is obtained only from the Napping data, i.e., from the X and Y coordinates of the *individual* configurations. This means that for each beer, there are 17 partial data points (one for each panelist), and that the representations in the consensus map are an average of the partial ones. This is exemplified visually in Figure 3, where, for clarity, we considered only three samples (chosen because their average point lies far from the origin in different directions). On a global level, these beers were perceived as different by the whole panel. However,

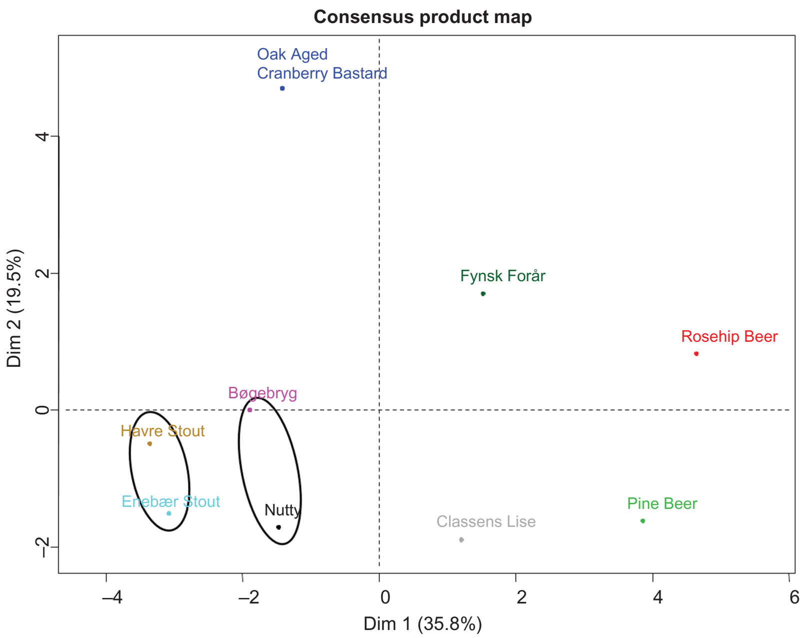

FIGURE 2 Consensus product map (Dim1 vs. Dim2) (color figure available online).

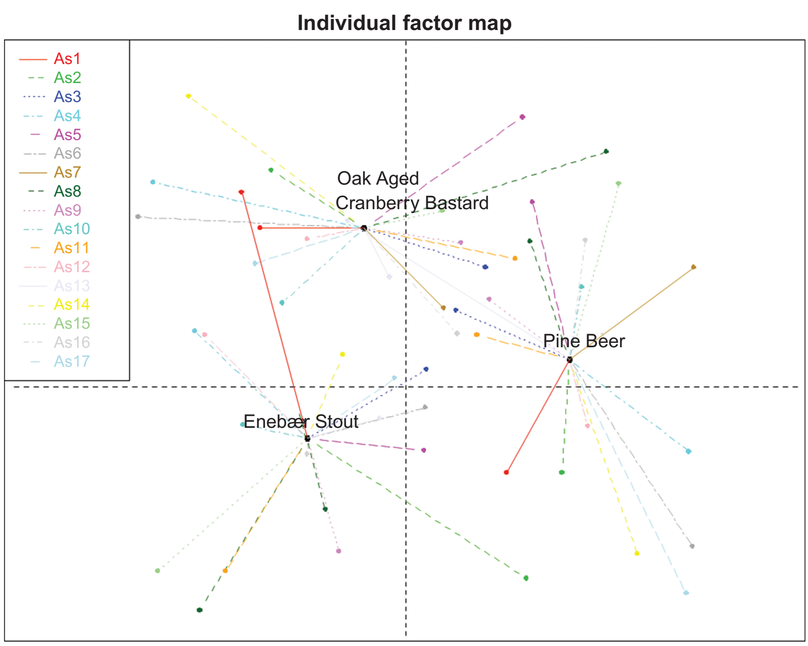

FIGURE 3 Representation of three beers obtained by averaging the partial 17 points. The partial positions for each panelist are shown in different colors and can be related to the average position (color figure available online).

superimposing the individual points show remarkable individual differences: for example, assessor 1 did not clearly discriminate between Oak Aged Cranberry Bastard and Enebær Stout but opposed both of them to the Pine Beer. Vice versa, assessor 8 placed the Pine Beer and Oak Aged Cranberry Bastard close to each other and opposed them to Enebær Stout. These kinds of individual differences are to be expected in a Napping task, where individuals are free to choose their own criteria for characterizing the samples. Thus, while the consensus profile provides a "compromise" configuration (Pagès, 2005), inspecting individual configurations can be interesting to discover what sensory characteristic mattered more for the individual consumers.

Subjects' and Dimensions' Influence

Inter-individual differences are also evident when looking at the subjects' representation (Figure 4): this plot has the two first MFA dimensions as the abscissa and ordinate. Each subject is then plotted in according to his or her weight with that particular dimension of the MFA model. Thus, the relative

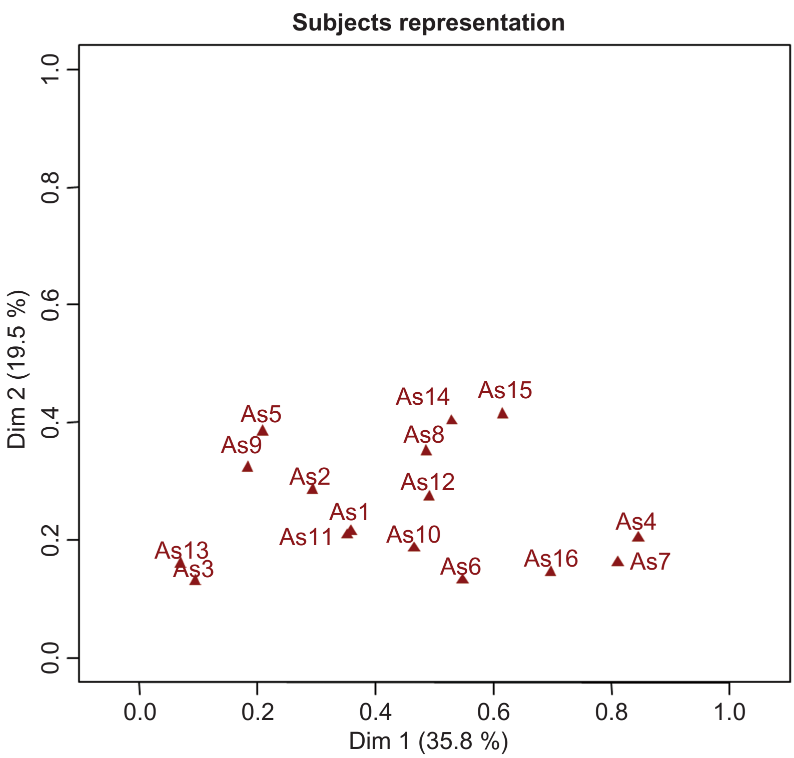

FIGURE 4 Representation of the 17 subjects. The coordinate of each subject along the two axes indicate the importance of that dimension given by the subject in his or her configuration (color figure available online).

importance given by each subject to each dimension (and to the underlying sensory characteristics) can be observed. Assessors 4 and 7 assess the samples as most different to each other along the first underlying dimension, whereas assessors 14 and 15 use dimension 2 the most. However, the subjects mostly differ in their relation to the first dimension, while not so much variation can be observed in dimension 2; we can conclude that the sensory differences responsible for differences within samples are the ones described by dimension 1 (as it was to be expected by looking at the consensus profile).

In a Napping test, inter-product differences are given as Euclidean distances, meaning that each product has an X and a Y on each panelist's sheet. These coordinates are different between assessors (as shown in Figure 3) and determine the formation of the MFA dimensions. Figure 5 shows how each individual panelist's sample coordinates are correlated with the first two dimensions. Correlation is indicated by the angle formed between the dimension and the vector; contribution is indicated by the vector length. These coordinates are not normalized in the constructions of the axes; in Figure 6, they appear as normalized to show their correlation with the MFA

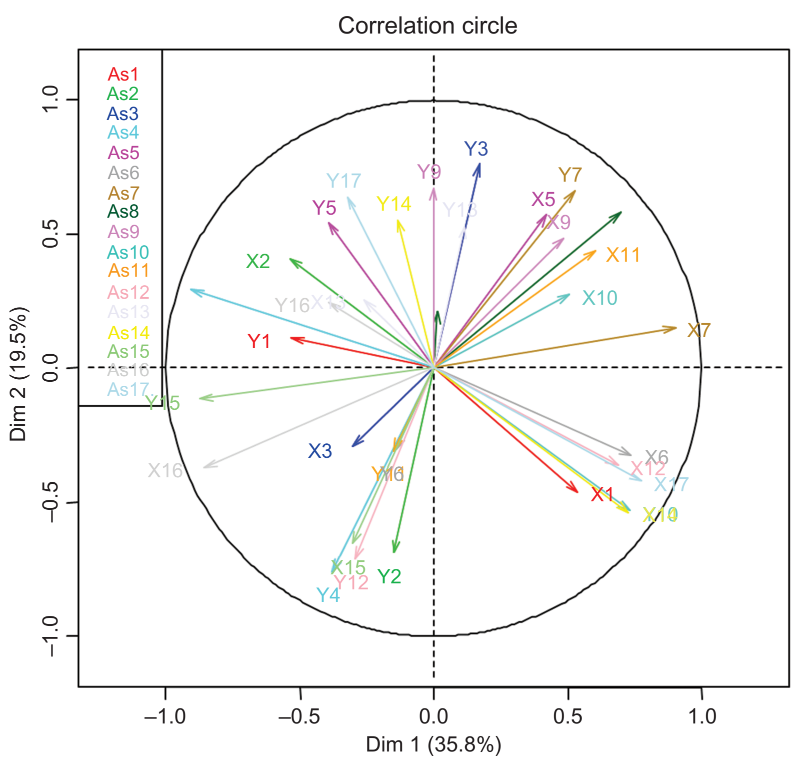

FIGURE 5 Representation of the individual axes of coordinates and their correlation with the first two MFA dimensions (color figure available online).

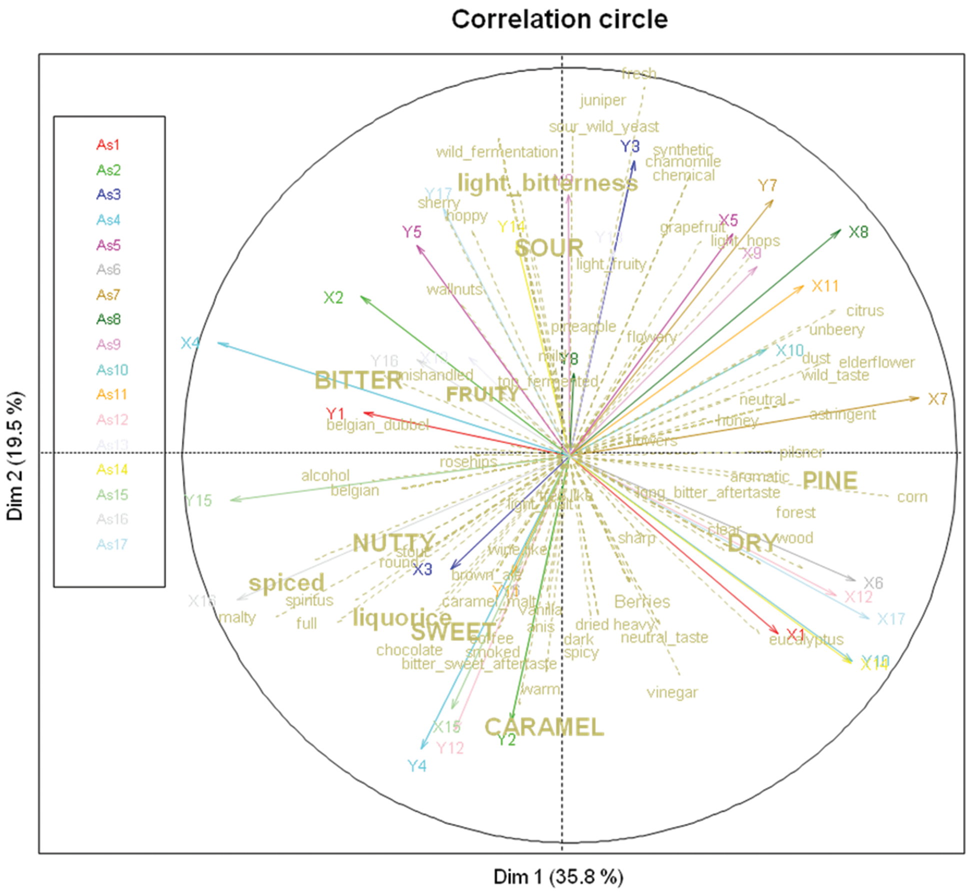

FIGURE 6 Representation of sensory descriptors and their correlation with the MFA dimensions (indicated by the corresponding vector). Terms in large fonts were used more frequently (uppercase: >30 times; lowercase: >20 times). Descriptors used only once and/or of hedonic nature have been omitted (color figure available online).

dimensions. Visual inspection indicates that the X vectors have higher correlations with the first dimension. However, the high numbers of panelists inhibits an easy-to-read plot. We computed some simple descriptive statistics to ease the interpretation: on average, X coordinates had both larger range (X = 47.72; Y = 26.90) and standard deviation (X = 17.50; Y = 9.35) than the ordinates. The fact that the horizontal dimension is more used than the vertical one is a recurrent result in the Napping test, which is framed by the fact that the tablecloth is of rectangular shape with a longer horizontal side. However, it is conjectured that this greater use of the horizontal dimension corresponds to a more significant sensory dimension for the subject; thus the X vectors will correspond to the most important sensory characteristic for the subject (Pagès, 2005), regardless of which MFA dimension they are related to.

Descriptors Representation and Interpretation

The analysis thus far conducted has been concerned with how the subjects discriminate the products. The present section will discuss the underlying sensory differences.

Once a consensus profile has been computed, it can be interpreted according to pre-existing knowledge of the sample set. However, since we combined Napping with a descriptive task (Ultra-Flash Profiling), sensory directions could be drawn directly from the subjects' elicited descriptions.

Figure 6 shows the representation of the sensory descriptors and their correlation with the MFA dimensions (though they are not used for constructing the axes). The plot shows that the dimension opposes bitter and fruity to "woody" notes ("pine," "wood," "forest," etc.) and flowery notes. Sourness is very positively loaded on dimension two, as opposed to sweetness. It is now possible to interpret our consensus profile's underlying properties. Inspecting Figure 2 and Figure 6 simultaneously revealed the sensory characteristics responsible for the product differences. Along the first MFA dimension, we find on the lower left quadrant Cluster 1 and Cluster 2, which, when combined, contain four beers: Bøgebryg, Havre Stout, Enebær Stout, and Nutty. These beers are correlated to sensory descriptors such as "nutty," "licorice," "malty," "coffee," "smoked," and the beer type descriptors "stout" and "brown ale." These two clusters basically group all the dark beers together (two stouts and two dark ales), which are opposed to the others. The sensory descriptors correlated with these clusters are consistent with the beer styles they belong to. Within-cluster differences are less clear; however, the two stouts (Cluster 1) were perceived as more similar than the other ales.

On the top left quadrant, we find Oak Aged Cranberry Bastard, with the highest scores on dimension 2 and opposed to the rest of the beers in the first two dimensions. Oak Aged Cranberry Bastard is a fruit beer brewed with cranberries and produced by spontaneous fermentation, as are some Belgian beers. This latter characteristic was perceived by some subjects, and the descriptors "wild fermentation" and "sour wild yeast" were positively correlated with this beer. No panelist could recognize the taste of cranberry as such, but the sensory descriptors most positively associated with this beer are "sour" and "light bitterness," plausible characteristics of the taste of cranberry. Classens Lise, a pale ale with added honey and chamomile, is located on the lower right corner, moderately correlated with the first dimension. Its position was close to the origin, indicating that none of the first two dimensions modeled this beer well; however, one of its ingredients is honey, and indeed, it correlates positively to the descriptor "sweet" and negatively to "sour." A third dimension (not included in this analysis) distinguished Classens Lise from the remainder of the beers. In the same lower right quadrant is the Pine Beer. This was an experimental one:

a pilsner with added pine needle flavoring. This beer is positively loaded on dimension 1, where the woody characteristics are strong, highly correlated with "descriptors such as "pine," "woody," "forest," "astringent," and "dry," showing that this pine-woody dimension was clearly perceived by most panelists.

On the top-right quadrant we find Fynsk forår, a pale ale with added elderflower. It is positively loaded on both dimensions, correlated to descriptors such as "flowery" and "elderflower." Finally, the other experimental beer, a pilsner with added rosehip powder, is also positively correlated to dimension one and somewhat correlated with flowery notes. The descriptor "pilsner" also is highly loaded on dimension 1 and correlated with Pine Beer and Rosehip Beer (the two pilsner beers in the sample set).

Individual vs. Average: Superimposed Representations and Inter-Group Differences

This section addresses the second aim of the study: comparison of expert and novice consumers' ability to perform a Napping task.

In a Napping test, the agreement of one subject with the overall product map can be evaluated by superimposing his or her own configuration with the average one, as in the example shown in Figure 1. This characteristic is especially advantageous—whether working with consumers or trained panelists—since it allows the researcher to visually inspect if one subject perceived the products similarly or differently from the consensus configuration. As explained earlier, a measure of fit between the two configurations can be obtained by computing the *RV* coefficient. The higher the latter, the closer the individual configurations will be to the consensus configuration.

One of the tested hypotheses was that people with higher knowledge of beer would profile the samples more consistently, i.e., have larger *RV* values. To test that, the panelists were divided into two groups: experts and novices. The mean *RV* coefficient for the brewmasters group was higher than the other group's mean. The *t*-test revealed significant differences between the means of the two groups ($p = 0.0125$).

The obtained results (summarized in Table 2) support our hypothesis.

TABLE 2 Mean and Standard Deviations Computed for the Two Groups of Assessors

RV coefficients	Mean	S.D.
Experts (n = 8)	0.618	0.167
Novices (n = 9)	0.405	0.169
Unpaired t-test showed significant difference between the two groups ($p = 0.01252$)		

DISCUSSION AND CONCLUSIONS

The first and foremost aim of this study was to test the applicability of Napping—performed by untrained panelists—to discriminate among a sample of Danish special beers. With regard to that, the experiment was successful. The samples were discriminated and the method provided interpretable results with regard to the sensory dimensions responsible for differences between beers. Most of our subjects positioned the samples according to either the beer style or the specific flavor added. Overall, the first dimension could be seen as separating lagers and pale ales from the four dark ales.[3] The influence of the special ingredient was important especially for the two experimental beers, and for the beer most correlated with the second MFA dimension (Oak Aged Cranberry Bastard).

Furthermore, Napping allowed us to look at the differences between the subjects and the level of agreement with the general consensus via the *RV*-coefficient. We found that, on average, experts had configurations more consistent with the consensus profile. This suggests that the precision is higher with product experts. This conclusion must be considered with caution; our results, however significant, refer to a small population. Moreover, the choice of the type of panelists to use could be related more to the specific aim of the test. Larger and more systematic studies are needed to better understand the effect of product knowledge on a subject's performance in a Napping test.

From a business-oriented perspective, it is important to stress that (partial) Napping is a very fast technique. Each experimental session took no more than 30 minutes (plus 30 minutes of preparation), with no prior training required. Moreover, the task was very well received by the subjects, who generally enjoyed the experience as a sort of tasting game.

In our view, the combination of Napping and Ultra-Flash profile applied in this study is especially interesting because it relies directly on the subjects' perceptions, letting them decide autonomously what are the most important sensory dimensions. In this sense, it is possible to say that this technique provides both *quantitative* and *qualitative* information, as it has been observed about other rapid methods (Chollet et al., 2011). This characteristic is particularly important in studies that aim at understanding what really matters for consumers, or, in other words, where external validity is a key issue (Garber, Hyatt, & Starr, 2003). Thus, Partial Napping could also be employed for selecting relevant descriptors to be used subsequently in, for example, a conventional profile, and/or to select subset of products for subsequent

[3] With regard to the beers in clusters 1 and 2, it should be acknowledged that the subjects might have been influenced by the color (though they were instructed to concentrate only on smell and taste), since clear glasses were used during the Napping task. The color of a product is known to affect the perception of other sensory characteristics (Lawless & Heymann, 2010). The sensory descriptors elicited, however, match our previous knowledge of the samples and the commercial descriptions by the producer.

larger-scale consumer tests. These characteristics make Napping a versatile method, useful in a variety of settings both in combination with other sensory profile techniques or as a stand-alone. Furthermore, the speed and low cost of this method make it a valuable opportunity especially for SMEs in the food industry, which seldom have the resources or the access to conventional sensory panels.

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